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Présenté par:

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Thème :

Contribution à la Commande Intelligente d'un Système Hybride (Éolienne/Photovoltaïque) Connecté au Réseau Électrique

Soutenue publiquement devant le jury composé de:

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Academic Year**:** 2025/2026

PEOPLE'S DEMOCRATIC REPUBLIC OF ALGERIA
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DOCTORAL THESIS

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in:Electrical Engineering

Speciality: Electrical Engineering and Electrical Control

Presented by:

Mujammal Ahmed Hasan Mujammal

Thesis Title:

Contribution of intelligent Control of Hybrid Renewable Energy Sources (Wind/ Photovoltaic) Connected to Grid

Defended in front of a jury composed of:

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Dedication

After a long journey of research and living away from my homeland, I would like to express my deepest gratitude and sincere appreciation to my beloved father, may he rest in peace, who raised me on noble values and high principles and was a guiding light throughout my academic and personal life. I also extend my heartfelt thanks to my dear mother, may God protect her, for her unwavering support, patience, and constant encouragement.

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Table 1: List of Abbreviations Used in the Thesis

Abbreviation	**Definition**
AI	Artificial Intelligence
ABC	Artificial Bee Colony
AC	Alternating Current
ACO	Ant Colony Optimization
ANN	Artificial Neural Network
COA	Centroid of Area
CNN	Convolutional Neural Network
DC	Direct Current
DPC	Direct Power Control
DSP	Digital Signal Processor
EMS	Energy Management System
EP	Error Power
FLC	Fuzzy Logic Controller
FL	Fuzzy Logic
FACTS	Flexible AC Transmission Systems
GWO	Grey Wolf Optimization
HCS	Hill Climbing Search
HRES	Hybrid Renewable Energy System
IC	Incremental Conductance
IoT	Internet of Things
LVRT	Low Voltage Ride Through
ML	Machine Learning
MPPT	Maximum Power Point Tracking
MPP	Maximum Power Point
NN	Neural Network
NM	Negative Medium (Fuzzy set)
NB	Negative Big (Fuzzy set)
NS	Negative Small (Fuzzy set)
PB	Positive Big (Fuzzy set)
PM	Positive Medium (Fuzzy set)
PS	Positive Small (Fuzzy set)
P&O	Perturb and Observe
PLL	Phase Locked Loop
PV	Photovoltaic
PR	Performance Ratio
RLC	Resistor–Inductor–Capacitor
RNN	Recurrent Neural Network
Rs	Series Resistance
Rsh	Shunt Resistance
SCADA	Supervisory Control and Data Acquisition
SMC	Sliding Mode Control
SNN	Spiking Neural Network
SVM	Space Vector Modulation
SVPWM	Space Vector Pulse Width Modulation
VSC	Voltage Source Converter
VOC	Open Circuit Voltage
WECS	Wind Energy Conversion System
WT	Wind Turbine
ZE	Zero Error (Fuzzy set)

Table 2: Complete List of Symbols with Definitions and Units

Symbol	Definition	Unit
I	Output current of PV cell	A (Ampere)
I_{ph}	Photogenerated current	A
I_D	Diode current	A
I_{sh}	Shunt leakage current	A
I_0	Reverse saturation current	A
I_{sc}	Short-circuit current	A
I_{mp}	Current at maximum power point	A
V	Voltage across PV cell	V (Volt)
V_{oc}	Open-circuit voltage	V
V_{mp}	Voltage at maximum power point	V
P	Electrical power output ($P = VI$)	W (Watt)
G	Solar irradiance	$\mathrm{W/m^2}$
q	Electron charge	C (Coulomb)
K	Boltzmann constant	J/K
T	Cell temperature	K (Kelvin)
E_g	Bandgap energy	eV (electron volt)
R_s	Series resistance	Ω (Ohm)
R_{sh}	Shunt resistance	Ω
dV/dI	Differential voltage-current slope	V/A
η	Efficiency	- (dimensionless)
C_1, C_2	Capacitors in converter	F (Farad)
L	Inductance in boost converter	H (Henry)
f_s	Switching frequency	Hz
R_{Load}	Load resistance	Ω
D	Duty cycle of converter	-
$\mu(x)$	Membership degree	-
a_1, a_2, a_3, a_4	MF parameters (fuzzy logic)	-
γ_k	Gaussian spread in MF	-
$center_k$	Center of Gaussian MF	-
t	Input to sigmoid MF	-
$sig(t)$	Output of sigmoid function	-
λ	Tip-speed ratio	-
β	Pitch angle	Degrees (°)
C_p	Power coefficient of wind turbine	-
ρ	Air density	$\mathrm{kg/m^3}$
R	Blade radius	m
A	Swept area	$\mathrm{m^2}$
V_w	Wind speed	m/s
T_m	Mechanical torque	$\mathrm{N \cdot m}$
T_e	Electromagnetic torque	$\mathrm{N \cdot m}$
Ω_t	Turbine angular speed	rad/s
Ω_m	Generator angular speed	rad/s
J_t, J_m	Moment of inertia	$\mathrm{kg \cdot m^2}$
f	Friction coefficient	$\mathrm{N \cdot m \cdot s}$
p	~~Pole pairs~~	-
R_s, R_r	Stator and rotor resistances	Ω
L_s, L_r, L_m	Inductances	H
ϕ_s, ϕ_r	Magnetic flux	Wb (Weber)
$V_{ds}, V_{qs}, V_{dr}, V_{qr}$	d-q axis voltages	V
$I_{ds}, I_{qs}, I_{dr}, I_{qr}$	d-q axis currents	A
ω_s, ω_r	Angular frequencies	rad/s
δ	Flux angle difference	rad

Abstract

The increasing depletion of fossil fuel resources and rising environmental concerns have accelerated the global transition toward renewable energy systems. Among available alternatives, hybrid solar–wind energy systems offer enhanced reliability by mitigating the inherent intermittency of individual renewable sources. However, their large-scale deployment faces significant challenges related to power variability, system efficiency, and grid integration. This thesis investigates advanced intelligent control strategies to optimize energy generation and ensure stable operation of hybrid solar–wind systems. Emphasis is placed on artificial intelligence–based techniques, including neural networks, fuzzy logic,and data-driven algorithms, for improved maximum power point tracking and energy management. Advanced power electronics and control methods, such as voltage source converters and direct power control, are employed to enhance power quality and grid stability. The proposed approaches demonstrate superior adaptability under rapidly changing environmental conditions. Simulation and analytical results validate the effectiveness of the developed control strategies. The findings contribute to improved efficiency, reliability, and sustainability of hybrid renewable energy systems. This research supports the development of smart, resilient, and environmentally friendly power systems for future energy networks.

Keywords: Renewable Energy Sources, Photovoltaic, Wind Energy, Intelligent Control, M5P, Fuzzy System, Hybrid Energy Sources

الملخص

أدى الاستنزاف المتزايد لموارد الوقود الأحفوري وتزايد المخاوف البيئية إلى تسريع التحول العالمي نحو أنظمة الطاقة المتجددة. من بين البدائل المتاحة، توفر أنظمة الطاقة الشمسية والرياح الهجينة موثوقية معززة من خلال التخفيف من التقطع المتأصل في مصادر الطاقة المتجددة الفردية. ومع ذلك، يواجه نشرها على نطاق واسع تحديات كبيرة تتعلق بتقلب الطاقة وكفاءة النظام وتكامل الشبكة. تبحث هذه الأطروحة في استراتيجيات التحكم الذكية المتقدمة لتحسين توليد الطاقة وضمان التشغيل المستقر لأنظمة الطاقة الشمسية والرياح الهجينة. وينصب التركيز على التقنيات القائمة على الذكاء الاصطناعي، بما في ذلك الشبكات العصبية والمنطق الضبابي والخوارزميات القائمة على البيانات، من أجل تحسين تتبع نقطة الطاقة القصوى وإدارة الطاقة. يتم استخدام إلكترونيات الطاقة المتقدمة وطرق التحكم، مثل محولات مصدر الجهد والتحكم المباشر في الطاقة، لتحسين جودة الطاقة واستقرار الشبكة. تظهر الأساليب المقترحة قابلية تكيف فائقة في ظل الظروف البيئية المتغيرة بسرعة. تؤكد نتائج المحاكاة والتحليل فعالية استراتيجيات التحكم المطورة. تساهم النتائج في تحسين كفاءة وموثوقية واستدامة أنظمة الطاقة المتجددة الهجينة. تدعم هذه الأبحاث تطوير أنظمة طاقة ذكية ومرنة وصديقة للبيئة لشبكات الطاقة المستقبلية

الكلمات المفتاحية: مصادر الطاقة المتجددة، الطاقة الكهروضوئية، طاقة الرياح، التحكم الذكي، النموذج الخامس من شجرة القرارات، النظام الضبابي، مصادر الطاقة الهجينة

Résumé

L'épuisement progressif des ressources fossiles et les préoccupations environnementales croissantes ont accéléré la transition mondiale vers les énergies renouvelables. Les systèmes hybrides PV–éolien constituent une solution prometteuse pour pallier l'intermittence inhérente aux sources renouvelables individuelles et améliorer la fiabilité de la production énergétique. Toutefois, leur intégration à grande échelle soulève des défis majeurs liés à la variabilité de puissance, à la stabilité du système et à l'interconnexion au réseau. Cette thèse propose des stratégies de commande intelligentes avancées visant à optimiser la production d'énergie et à renforcer la stabilité des systèmes hybrides PV–éolien. Des techniques basées sur l'intelligence artificielle, telles que les réseaux de neurones, la logique floue et les approches orientées données, sont exploitées pour améliorer le suivi du point de puissance maximale et la gestion énergétique. Des méthodes avancées d'électronique de puissance et de commande, notamment les convertisseurs à source de tension et la commande directe de puissance, sont intégrées afin d'améliorer la qualité de l'énergie et la stabilité4 du réseau. Les résultats de simulation démontrent la robustesse et l'efficacité des approches proposées. Cette recherche contribue au développement de systèmes énergétiques durables, intelligents et résilients pour les réseaux électriques de nouvelle génération.

Mots-clés : Sources d'énergie renouvelables, Photovoltaïque, Énergie éolienne, Contrôle intelligent, M5P, Système flou, Sources d'énergie hybrides

General Introduction

The rapid depletion of fossil fuel reserves and growing environmental concerns have driven a global shift toward renewable energy sources [150]. The traditional reliance on coal, oil, and natural gas for power generation has led to severe ecological consequences, including greenhouse gas emissions, air pollution, and climate change. As nations strive to meet international climate agreements such as the Paris Accord, the urgency of transitioning to clean and sustainable energy solutions has never been greater. Renewable energy sources, particularly wind and solar power, have gained widespread recognition as viable alternatives due to their abundance, sustainability, and minimal environmental impact. However, despite their potential, several technical and economic challenges hinder their large-scale integration into power grids [52].

One of the key obstacles in renewable energy deployment is its intermittent and variable nature. Solar photovoltaic (PV) systems [152] rely on sunlight, making their output dependent on weather conditions [66], seasonal variations, and geographical location. Similarly, wind energy systems [32] are influenced by wind speed fluctuations, which can vary unpredictably. The inherent variability of these renewable sources can lead to grid instability, voltage fluctuations, and frequency deviations, posing challenges for maintaining a reliable and secure power supply [87]. To address these issues, hybrid renewable energy systems (HRES) [84] have emerged as a promising solution, combining different renewable sources to complement each other and improve overall energy generation efficiency [61].

Hybrid solar-wind systems [154], in particular, offer significant advantages over standalone renewable energy technologies. The complementary nature of solar and wind resources allows for a more stable and continuous energy supply—when solar radiation is low, wind speeds may be higher, and vice versa [11]. This synergy enhances system reliability and reduces dependence on energy storage solutions, which can be costly and require frequent maintenance. Moreover, hybrid systems can be designed for both standalone (off-grid) and grid-connected applications, making them versatile for various energy demands, from rural electrification to large-scale power generation [95].

While hybrid renewable energy systems present numerous advantages, their successful implementation requires advanced control strategies to optimize power generation, improve efficiency, and ensure seamless grid integration [110]. The efficiency of solar and wind systems is highly dependent on real-time control techniques, such as Maximum Power Point Tracking (MPPT), power electronics-based conversion, and smart energy management systems. Traditional MPPT techniques, such as Perturb and Observe (P&O) and Incremental Conductance (IC), have been widely used but often struggle to adapt to rapidly changing environmental

conditions. Recent advancements in artificial intelligence (AI) and machine learning have introduced innovative approaches to control and optimization, significantly enhancing the performance of renewable energy systems [53].

Artificial intelligence techniques, including artificial neural networks (ANNs) [5], fuzzy logic controllers (FLCs), and decision tree-based algorithms, have been extensively explored for renewable energy applications. These intelligent control methods can predict energy generation patterns, adapt to fluctuating environmental conditions, and optimize system performance in real time. AI-driven MPPT controllers, for example, offer superior tracking accuracy and faster response times compared to conventional methods, maximizing the power output of solar and wind systems. Additionally, data-driven predictive models can enhance energy forecasting, grid stability, and fault detection, leading to more resilient and efficient hybrid renewable energy systems [121].

Another crucial aspect of hybrid system implementation is the integration with existing power grids. Grid-connected hybrid renewable energy systems contribute to energy diversification, reducing reliance on conventional power plants and lowering overall carbon emissions. However, ensuring grid stability and power quality remains a major challenge. Voltage fluctuations, harmonics, and reactive power management are key technical issues that must be addressed. Advanced power electronics technologies, such as voltage source converters (VSCs)[77], space vector modulation (SVM) [35], and direct power control (DPC) [37], play a vital role in mitigating these challenges. Furthermore, intelligent energy management strategies enable optimal power dispatch, load balancing, and economic operation of hybrid systems within smart grids.

In addition to technical considerations, economic feasibility and policy frameworks play a significant role in the large-scale deployment of hybrid renewable energy systems [20]. The cost of solar PV panels and wind turbines has significantly decreased over the past decade, making renewable energy more competitive with conventional power sources [26]. However, initial capital investment, maintenance costs, and energy storage expenses remain key factors influencing adoption. Governments and regulatory bodies worldwide are implementing policies, incentives, and tariff mechanisms to encourage investment in renewable energy infrastructure. Net metering, feed-in tariffs, and carbon credits are some of the policy instruments used to promote hybrid renewable energy projects and facilitate their grid integration [140].

This research aims to contribute to the ongoing development of intelligent control strategies for hybrid solar-wind energy systems, focusing on optimizing energy generation, improving system stability, and enhancing grid integration. By leveraging advanced MPPT techniques, artificial intelligence-based control methodologies, and innovative power electronics solutions, this study seeks to address the technical challenges associated with hybrid renewable energy systems. The findings of this research will provide valuable insights into the practical implementation of smart control strategies, supporting the transition toward a more sustainable, efficient, and resilient energy future.

Through a comprehensive analysis of hybrid renewable energy systems, this thesis will explore cutting-edge advancements in AI-driven control, power management, and grid in-

teraction. By integrating state-of-the-art technologies, the research aims to pave the way for next-generation renewable energy solutions that can effectively meet the demands of modern power systems while ensuring environmental sustainability and economic viability. Ultimately, this work aspires to contribute to the global effort in achieving cleaner energy production, reducing carbon footprints, and promoting sustainable development in the energy sector.

Chapter 1

Introduction to Hybrid Renewable Energy Systems (Solar and Wind Power)

The global energy demand has been growing at an unprecedented rate due to industrial growth, urbanization, and the rising standard of living worldwide[90]. Nevertheless, this growing request presents crucial challenges, mainly due to the dependence on fossil fuels, which are both finite and major contributors to environmental degradation [150]. Fossil fuel-based energy production is responsible for the majority of greenhouse gas emissions, leading to climate change, global warming, air pollution, and a host of environmental and public health concerns. Given these alarming realities, the search for sustainable, renewable energy sources has become a priority for governments, organizations, and researchers globally [1]. Among the renewable energy options, solar and wind energy have emerged as two of the most promising solutions. Solar energy harnesses the power of sunlight through photovoltaic (PV) cells, while wind energy captures the kinetic energy of wind using turbines [56]. Both sources are clean, inexhaustible, and widely available, making them ideal for addressing the energy needs of the future. However, one of the primary challenges associated with solar and wind energy is their intermittent nature—solar energy generation depends on sunlight availability, and wind energy production is reliant on wind speed and conditions. This intermittency can make it difficult to ensure a consistent energy supply, especially in regions where either sunlight or wind is not constantly available. Hybrid Renewable Energy Systems (HRES) offer an innovative solution to this challenge by combining two or more renewable energy sources—most commonly solar and wind power—into a single system. HRES are designed to leverage the complementary characteristics of different energy sources to provide a more reliable and stable energy output. For instance, while solar energy is available during the day, wind energy might be more prevalent during the night or on cloudy days, allowing the two sources to balance each other out. This approach helps to mitigate the intermittency issue and ensures a more consistent supply of energy [25]. Moreover, hybrid systems are often integrated with energy storage solutions, such as batteries or hydrogen fuel cells, to store excess energy when production exceeds demand and supply it when energy generation is low. This further enhances the reliability and flexibility of the system. In addition to providing a steady energy supply, HRES contribute to reducing greenhouse gas emissions, decreasing reliance on fossil fuels, and promoting sustainable development. With advance-

ments in technology, the cost of implementing these systems is gradually decreasing, making them more accessible and economically viable for both grid-connected and off-grid applications. The potential of HRES extends beyond mere energy generation. These systems can play a pivotal role in the decentralization of energy production, bringing clean energy to rural and remote areas that are not served by the central grid [78]. For regions with limited energy infrastructure, HRES can provide a critical solution to energy poverty, improving access to electricity and supporting economic development. Despite the clear advantages, there are also challenges associated with the design, implementation, and optimization of HRES. These systems require careful planning, including site-specific analysis to determine the optimal mix of renewable energy sources, as well as advanced control strategies to manage the fluctuating energy outputs. Furthermore, the integration of energy storage solutions adds complexity to the system design, requiring sophisticated management algorithms to ensure efficient energy use. Ongoing research is focused on overcoming these challenges, improving system efficiency, and maximizing the potential of HRES in various applications. This chapter introduces the concept of hybrid renewable energy systems, emphasizing the importance of integrating solar and wind energy to address the global energy and environmental crises. It explores the benefits of combining multiple renewable sources to ensure energy reliability and stability, while also discussing the technical and economic challenges associated with these systems. By highlighting the potential of HRES, this chapter sets the foundation for further exploration of the design, control, and optimization strategies that can enhance the performance and feasibility of hybrid renewable energy systems in diverse contexts.

1.1 Background and Motivation

1.1.1 Global Energy Demand and Environmental Concerns

The global energy landscape is rapidly growing due to the increasing need for energy caused by population growth, urbanization, and economic effects. As the world becomes more industrialized and technologically developed, energy consumption is projected to increase significantly in the future decades. According to the International Energy Agency (IEA), the global energy demand is predicted to increase by about 25% by 2040 if present trends continue. Nevertheless, non-renewable energy sources, such as fossil fuels like coal, oil, and natural gas- still meet most of this energy market. These traditional sources are restricted, causing the depletion of natural resources and raising environmental troubles. Fossil fuel combustion remains the primary cause of greenhouse gas emissions (GHGs), responsible for global climate variations [146]. The increase in carbon dioxide CO_2 and other toxic emissions has led to increasing global temperatures, melting polar ice caps, climate disasters, weather circumstances, increasing sea levels, and loss of biodiversity. Furthermore, the dependence on fossil fuels has created other environmental challenges, involving air and water pollution, acid rain, and ecosystem degradation. Energy production from non-renewable resources is often tied to deforestation, habitat collapse, and freshwater resource depletion. To mitigate these adverse environmental effects, the global community is increasingly looking towards sustainable energy solutions. Sources of renewable energy, such as solar and wind power, supply a cleaner choice than fossil fuels, offering a significant decrease in CO_2 emissions and other pollutants. Moreover, renewable energy technologies are becoming more cost-useful, making them a possible choice for meeting the growing energy needs while handling environmental crises [138].

1.1.2 The Need for Renewable Energy Solutions

1. Resource Scarcity and Fossil Fuel Depletion: The global reliance on fossil fuels, such as coal, oil, and natural gas, has led to concerns about resource scarcity and eventual depletion. Fossil fuels are finite resources formed over millions of years from organic matter, and their extraction rates are far exceeding their natural replenishment. As global energy demand continues to rise, the availability of these resources is diminishing, creating uncertainty about the future supply of energy [40].

2. The depletion of fossil fuel reserves also contributes to economic instability, as fuel prices fluctuate due to market demands and geopolitical factors. Additionally, the environmental impacts associated with fossil fuel extraction, such as habitat destruction, air pollution, and greenhouse gas emissions, compound the need to find sustainable alternatives. These factors underline the importance of shifting toward renewable energy sources that are abundant, sustainable, and have a lower environmental footprint. By investing in renewable energy technologies, societies can address the issue of resource scarcity, reduce dependence on exhaustible energy sources, and pave the way for a more resilient and sustainable energy future.

3. Finite Resources: Since fossil fuels are non-renewable, the amount of oil, coal, and natural gas in each barrel, ton, or cubic meter that is used up depletes the reserves of these fuels. In many regions of the world, "peak oil" has already been reached, indicating the start of a drop in oil supply. Accessing these resources will cost more in terms of the environment since extraction will become more challenging. Examples of such extractions are oil extraction from tar sands and deep sea drilling, both of which have negative environmental effects.

4. Energy Security: Dependence on fossil fuels puts nations without their energy resources in a precarious position where they must import energy from politically unstable areas. This dependence on outside energy sources makes the country more susceptible to fluctuations in prices, trade disputes, and disagreements over who has access to energy resources. Countries will confront ever more difficulties with energy security as fossil fuel supplies develop scarcer.

5. Health and Environmental Issues: The primary source of greenhouse gases (GHGs), which are responsible for the acceleration of global climate change [50], is still the combustion of fossil fuels. Using fossil fuels not only exacerbates global warming but also has serious negative effects on the environment and human health. Fossil fuel consumption is responsible for approximately 75% of global CO_2 emissions, contributing significantly to greenhouse gas buildup in the atmosphere. This rise in CO_2, methane CH_4, and nitrous oxide N_2O traps heat, leading to global warming. Without a significant shift in the energy mix, the world will exceed the 1.5°C to 2°C temperature increase limit set by the Paris Agreement, causing irreversible climate damage. Burning fossil fuels also results in severe air pollution, releasing harmful pollutants like sulfur dioxide SO_2, nitrogen oxides NO_x, and particulate matter (PM), which degrade air quality. This pollution leads to millions of premature deaths annually due to respiratory and cardiovascular illnesses, particularly in urban areas of rapidly industrializing countries, where it reduces life expectancy and strains healthcare systems. Fossil fuel extraction and processing, especially through methods like hydraulic fracturing (fracking) and oil drilling, contribute

to water contamination. Oil spills and the disposal of industrial effluents from fossil fuel industries further pollute water sources, threatening ecosystems and communities reliant on clean water. Additionally, mining and drilling operations devastate ecosystems by destroying forests, wetlands, and other natural habitats, leading to biodiversity loss and disruption of ecological balance.

6. Climate Change and Extreme Weather Events: Global climate change is now commonly regarded as one of the most important issues of the twenty-first century. The ongoing rise in global temperatures has far-reaching consequences for the world, leading to increasingly frequent and severe extreme weather occurrences that include Rising ocean temperatures are intensifying tropical storms, such as hurricanes, cyclones, and typhoons, resulting in more destructive weather events. These storms cause catastrophic flooding, widespread property destruction, and significant loss of life. The severity of these storms is closely linked to the ongoing effects of climate change. Global warming is also driving more frequent and severe heatwaves, which pose serious health risks, especially for vulnerable populations. Along with heatwaves, prolonged droughts are becoming more common, negatively impacting agriculture, water supply, and food security. These droughts threaten the stability of essential resources needed for human survival. Additionally, the melting of glaciers and polar ice caps is causing sea levels to rise, which poses a grave threat to coastal regions. Flooding and storm surges are endangering low-lying island nations and coastal megacities, making them increasingly vulnerable to natural disasters. These climate impacts highlight the urgent need to reduce dependence on fossil fuels and shift to clean, renewable energy sources.

7. Sustainability and Energy Transition: Renewable energy solutions have become the most promising option for achieving long-term sustainability, energy security, and environmental protection. Unlike fossil fuels, renewable sources such as solar, wind, hydropower, and geothermal are inexhaustible, providing abundant energy without depleting natural resources. They are also environmentally friendly, emitting little to no greenhouse gases during operation and causing minimal environmental impact compared to the extensive damage caused by fossil fuel extraction and combustion. Moreover, renewable energy has become increasingly cost-effective due to technological advancements and economies of scale, with wind and solar power now among the most affordable energy sources globally. These factors make renewable energy a stable and financially sustainable alternative to volatile fossil fuel markets [39].

8. Global Initiatives and Renewable Energy Targets: Global initiatives and renewable energy targets have been established by governments, businesses, and international organizations to drive the shift toward a low-carbon economy and combat climate change. The Paris Agreement, ratified by 196 nations, aims to limit global warming to 1.5°C, requiring a rapid reduction in fossil fuel use and a swift transition to renewable energy. Many countries have also set national renewable energy targets to increase the share of renewables in their energy mix. For instance, renewable energy plays a key role in the European Union's goal of becoming carbon neutral by 2050, while China has committed to achieving carbon neutrality by 2060. Additionally, corporations are embracing renewable energy as part of their sustainability goals, with major companies like Google, Apple, and Amazon pledging to power their global operations entirely with renewable energy, setting an example for the private sector's role in the energy transition [50].

9. The Role of Hybrid Renewable Energy Systems: Even though separate renewable energy sources, such as solar and wind power, have many advantages, integrating them into hybrid systems can have even bigger benefits. Because hybrid solar-wind systems make use of these resources' complementing qualities, they are very appealing. The generation of solar energy peaks on sunny days, whereas wind energy is often highest at night or during overcast spells. This lessens reliance on fossil fuels and the requirement for backup power sources by ensuring a steadier and more regular energy supply. In addition to enhancing energy storage and grid integration, hybrid renewable energy systems are perfect for off-grid applications, rural electrification, and decentralized energy systems. Advanced control techniques, including Maximum Power Point Tracking (MPPT), energy management systems, and storage technologies, are integrated into hybrid systems to enhance efficiency and maintain power supply even under low sun or weak-wind conditions [84].

1.1.3 Role of Hybrid Renewable Energy Systems

Hybrid Renewable Energy Systems (HRES) play a crucial role in the global transition to clean energy by integrating multiple renewable sources such as solar, wind, and hydropower, along with energy storage systems like batteries or fuel cells. They provide numerous benefits, including enhanced energy reliability, environmental protection, cost efficiency, grid support, sustainability, and flexibility in energy management. By combining renewable sources, HRES mitigate the intermittency of individual systems. For instance, solar energy can be used during the day, while wind power compensates when solar energy is unavailable, ensuring a stable energy supply, particularly for off-grid or remote areas with fluctuating energy demands [139]. In terms of environmental benefits, HRES reduce greenhouse gas emissions by decreasing reliance on fossil fuels. Emission-free sources like solar and wind power, when combined with energy storage systems, help minimize the need for fossil fuel-based backup generators, promoting a cleaner, more sustainable energy generation system. While the initial investment in HRES may be high, they offer long-term cost savings through reduced operational and maintenance expenses and protect against fuel price fluctuations. Technological advancements are also lowering the cost of renewable energy components, making these systems increasingly viable economically. HRES also contribute to grid stability by providing distributed energy generation. In areas where centralized grids face challenges during peak demand or outages, hybrid systems can inject power into the grid, stabilizing frequency and voltage levels. In grid-connected scenarios, HRES prioritize the use of renewable energy and reduce grid dependence, improving overall energy efficiency. Additionally, these systems enhance energy access in remote regions where traditional grids are impractical, supporting sustainable development and contributing to the United Nations' Sustainable Development Goals (SDG 7) by providing clean, reliable energy. HRES also offer flexibility in energy management by allowing for customization based on local resources. Depending on the geographic location, HRES can emphasize specific renewable sources, such as solar power in desert areas or wind power in coastal regions. These systems also incorporate energy storage options, enabling better management of energy generation peaks and troughs, further improving efficiency and stability.

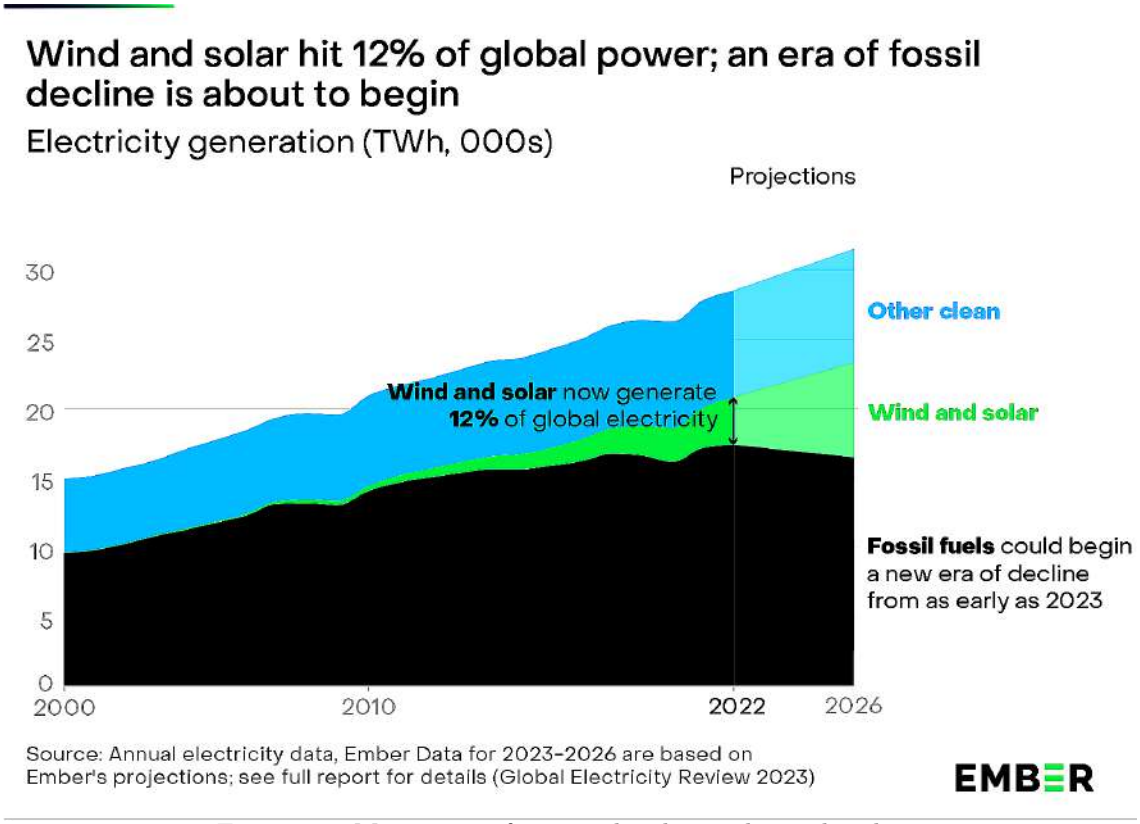


Figure 1.1: Main parts of a typical utility-scale wind turbine

1.2 Overview of Solar Energy Systems

Solar energy systems harness the energy of the sun through photovoltaic (PV) panels or concentrated solar power (CSP) technologies to generate electricity. Photovoltaic systems directly convert sunlight into electricity using semiconductor materials, such as silicon, which excite electrons when exposed to sunlight. This process, known as the photovoltaic effect, produces clean and renewable energy without emissions or fuel consumption. CSP systems, on the other hand, use mirrors or lenses to concentrate sunlight onto a small area to generate heat, which then drives a turbine to produce electricity. Solar energy systems are widely used in both grid-connected and off-grid applications, offering flexibility for residential, commercial, and industrial uses. These systems provide a sustainable alternative to fossil fuels, helping reduce carbon footprints and contributing to the global shift toward clean energy. Advances in energy storage technologies, such as batteries, have further improved the efficiency and reliability of solar energy by allowing excess energy generated during the day to be stored for use during periods of low sunlight. The continued drop in solar technology costs has made solar energy increasingly competitive and accessible worldwide [116].

1.2.1 Solar Energy

Solar energy is the power derived from the sun's radiation, harnessed using technologies like photovoltaic (PV) cells, which convert sunlight into electricity, and concentrated solar power (CSP), which uses mirrors or lenses to focus sunlight to generate heat. It is a renewable and clean source of energy, making it a key player in the global transition towards sustainable

energy systems [18]. Solar energy refers to the radiant light and heat from the sun that can be captured and utilized for various purposes, most notably electricity generation, heating, and even fuel production. Photovoltaic cells are commonly used to directly convert sunlight into electricity, while thermal systems like CSP focus sunlight to produce high temperatures that drive turbines for power generation. Abundance: The Earth receives about 173,000 terawatts of solar energy from the sun annually, which is vastly more than the total global energy consumption. If properly harnessed, solar energy could meet the world's electricity needs many times over, making it one of the most abundant energy sources available. Environmental Impact: Solar energy systems produce no greenhouse gases during their operation, offering a way to reduce carbon emissions and air pollution. This clean energy source plays a crucial role in combating climate change and advancing environmental sustainability. Economic and Social Benefits: Solar energy is becoming increasingly cost-effective as technology improves and production costs decrease. This makes solar a viable solution for both developed and developing regions, helping to provide affordable, decentralised electricity while creating jobs in manufacturing, installation, and maintenance. Energy Security: Solar energy systems, particularly those that are distributed and paired with energy storage solutions, can increase energy security by reducing reliance on fossil fuels and making local energy production more resilient to disruptions. While solar energy offers enormous potential, challenges such as variability in sunlight and land requirements for large-scale systems need to be addressed. However, advancements in energy storage technologies and solar panel efficiency continue to make solar energy a growing part of the world's energy mix.

1.2.2 Solar Photovoltaic (PV) Technology

Solar Photovoltaic (PV) technology is a method of generating electrical power by converting sunlight directly into electricity using semiconducting materials that exhibit the photovoltaic effect. This technology has emerged as one of the most promising renewable energy sources due to its scalability, environmental friendliness, and decreasing costs. PV systems can be utilized in a wide range of applications, from small-scale residential installations to large-scale utility projects [125].

1. Principles of Operation
   At the core of PV technology is the photovoltaic cell, typically made from silicon-based semiconductors. When photons from sunlight strike the surface of a PV cell, they may transfer their energy to electrons within the semiconductor material. This energy transfer allows electrons to break free from their atomic bonds, creating electron-hole pairs. The internal electric field within the cell, established by the junction of p-type and n-type semiconductors, drives these free electrons toward conductive metal contacts, generating a direct current (DC). By connecting multiple cells in series and parallel configurations, the voltage and current can be scaled to meet specific energy requirements [145].

2. Types of Photovoltaic Technologies PV technologies can be broadly categorised based on the materials and manufacturing processes used [45]:

   Monocrystalline Silicon Cells: Made from single-crystal silicon, these cells offer high efficiency and longevity but are relatively expensive due to the intricate manufacturing process, as shown in Figure 1.2.

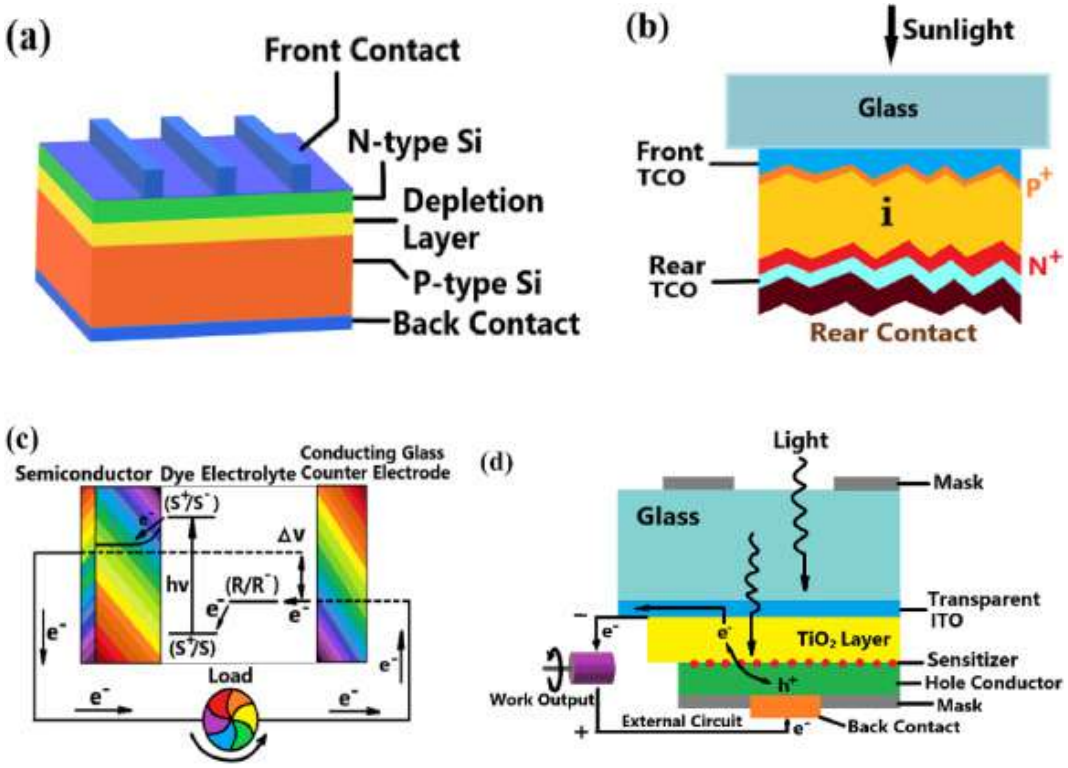


Figure 1.2: Monocrystalline Silicon Cells

Polycrystalline Silicon Cells: Composed of multiple silicon crystals, these cells are less efficient than monocrystalline but are more cost-effective, making them popular in residential applications, as shown in Figure 1.3.

Thin-Film Solar Cells: Utilizing materials like amorphous silicon, cadmium telluride, or copper indium gallium selenide, thin-film cells are less efficient but can be produced at lower costs and with more flexibility in applications, including building-integrated photovoltaics as shown in Figure 1.4.

Emerging Technologies: Innovations such as perovskite solar cells and organic photovoltaics are under development, aiming to reduce costs further and increase versatility, though they are not yet widely commercialized.

3. Components of a PV System
A complete PV system includes several components to ensure efficient energy conversion, safety, and compatibility with the electricity grid:

- Solar Panels (Modules): Assemblies of PV cells encapsulated to protect against environmental factors.
- Inverters: Devices that convert the generated DC into alternating current (AC) compatible with the grid or local usage. Advanced inverters can also perform maximum power point tracking (MPPT) to optimize the power output.
- Mounting Structures: Mechanical systems that secure PV panels at optimal angles and orientations to maximize solar exposure. These can be fixed or include tracking mechanisms that follow the sun's path.

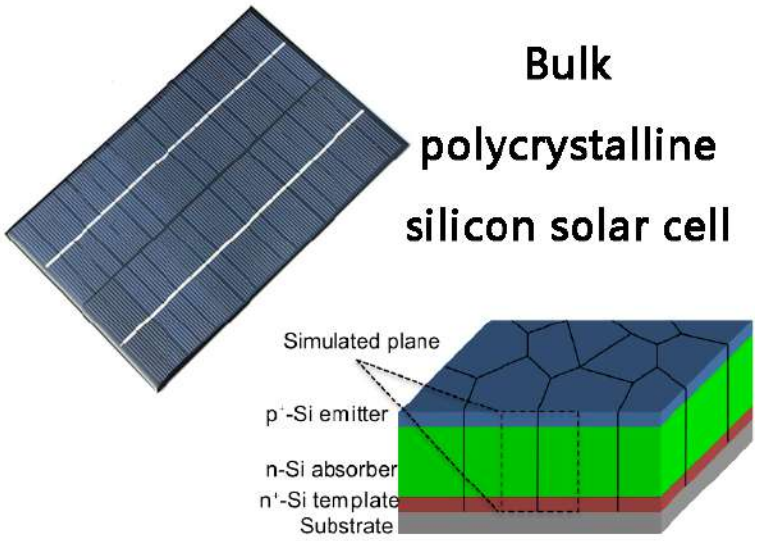


Figure 1.3: Polycrystalline Silicon Cells

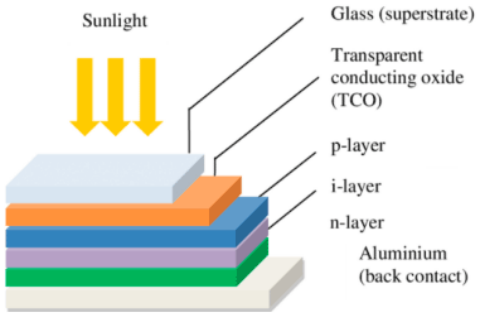


Figure 1.4: Polycrystalline Silicon Cells

- Energy Storage Systems: Batteries may be integrated to store excess energy for use during periods of low sunlight, enhancing the reliability of the PV system.
- Monitoring and Control Systems: Equipment and software that track performance, detect faults, and allow for intelligent control strategies, especially important in hybrid and grid-connected systems

4. Integration with the Electrical Grid: Grid-connected PV systems supply electricity directly to the utility grid, reducing energy consumption and potentially providing surplus power back. Key aspects include compliance with interconnection standards to ensure safe and efficient grid operation, as well as economic mechanisms like net metering and feed-in tariffs that offer financial incentives for system owners. Advanced smart inverters play a crucial role in stabilizing the grid by regulating voltage, frequency, and reactive power. However, challenges such as the intermittency of solar power, efficiency losses due to environmental factors, and the environmental impact of manufacturing PV cells must be addressed. Solutions like energy storage, proper system design, and sustainable manufacturing practices are essential for improving system performance and minimiz-

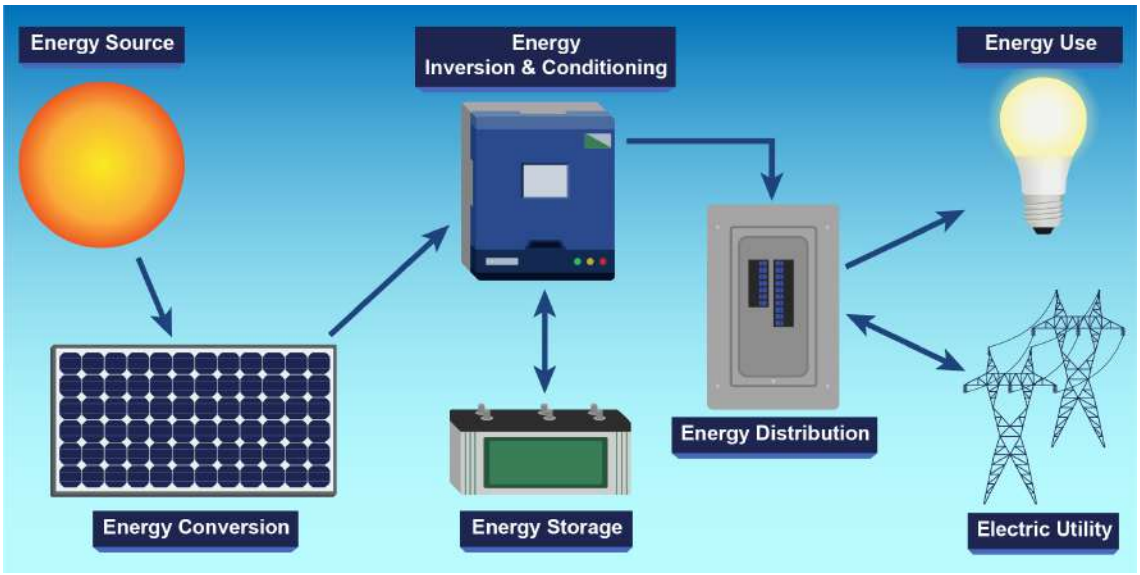


Figure 1.5: Components of a PV System

ing environmental impacts [149]. Role in Hybrid Energy Systems:In hybrid systems combining wind and photovoltaic sources, PV technology complements wind energy by offsetting the variability of each source. Solar panels can generate electricity during sunny, calm days when wind turbines may produce less power, while wind turbines can compensate during cloudy, windy conditions. Intelligent control strategies are essential in these systems to manage energy flows, optimize overall efficiency, and ensure seamless integration with the electricity grid. By leveraging advanced control algorithms, such as those based on artificial intelligence and machine learning, hybrid systems can dynamically adjust to changing environmental conditions and load demands. This results in improved reliability, maximized energy harvest, and enhanced grid support capabilities.

1.2.2.1 Working Principles of Solar PV Systems

Solar Photovoltaic (PV) systems operate by harnessing the photovoltaic effect, where certain materials generate electricity when exposed to sunlight. When sunlight, composed of energy particles called photons, strikes the PV cells in a solar panel, it excites electrons in the semiconductor material, typically silicon. This creates an electric field within the PV cells, causing electrons to break free and generate direct current (DC) electricity. The DC electricity is then converted into alternating current (AC) by an inverter, making it suitable for use in homes or businesses and for feeding into the electrical grid. The electricity generated can be used immediately or stored in batteries for later use, and any excess energy can be sent back to the grid, making solar PV systems a clean, renewable, and sustainable energy solution [6].

1.2.2.2 Solar Energy Efficiency and Performance

Solar energy efficiency and performance are critical factors in determining the effectiveness of solar power systems. Here are some key points to consider:
Solar Panel Efficiency: refers to the percentage of sunlight that a solar panel can convert into usable electricity. Higher efficiency means that the panel can generate more power from the same amount of sunlight. Solar panel efficiency depends on several factors, including the

type of photovoltaic cells used (e.g., monocrystalline, polycrystalline, thin-film), the quality of the materials, and external conditions such as temperature, shading, and dust. Advances in solar technology continue to improve efficiency, which is crucial for maximizing energy output, especially in areas with limited space for solar installations.

1.2.2.3 Performance Factors

- **Temperature:** Solar panels can lose efficiency at high temperatures. Most panels have a temperature coefficient that indicates how much efficiency decreases with rising temperatures.
- **Angle and Orientation:** The angle at which panels are installed affects their exposure to sunlight. Optimal tilt and orientation can significantly enhance performance.
- **Shading:** Even partial shading can reduce the output of solar panels. Proper placement and the use of micro inverters or power optimizers can mitigate this issue.
- **Dirt and Debris:** Accumulation of dirt, dust, and debris can block sunlight and reduce efficiency. Regular cleaning can help maintain performance.

1.2.2.4 System Performance

- **Inverter Efficiency:** Inverters convert the direct current (DC) produced by solar panels into alternating current (AC) used in homes. High-quality inverters can have efficiencies of 95% or higher.
- **Overall System Efficiency:** This includes the efficiency of the solar panels, inverters, and other components. The overall system efficiency is typically lower than the individual component efficiencies due to losses in wiring and other factors.

1.2.2.5 Energy Yield

- **Capacity Factor:** This is the ratio of actual output over a period to the maximum possible output if the system operated at full capacity all the time. It varies based on location, weather, and system design.
- **Performance Ratio (PR):** This metric measures the quality of a solar power plant by comparing the actual energy output to the expected output under ideal conditions. A PR of 75-85% is considered good.

1.2.2.6 Technological Advances

- **Bifacial Panels:** These panels can capture sunlight from both sides, potentially increasing energy generation.
- **Tracking Systems:** Solar trackers adjust the position of panels throughout the day to follow the sun, improving energy capture.
- **Emerging Technologies:** Research is ongoing into new materials (like perovskite solar cells) and methods to enhance efficiency and reduce costs.

1.2.2.7 Environmental Impact

Solar energy is a clean, renewable resource that reduces greenhouse gas emissions and dependence on fossil fuels. However, the production and disposal of solar panels can have environmental implications that need to be managed [117]. Here is a table illustrating the global solar energy usage (in terawatt-hours, TWh) over the last 5. Key Insights:

Table 1.1: Global Solar Energy Usage Over the Years

Year	Global Solar Energy Usage (TWh)
2019	724
2020	855
2021	1 030
2022	1 300
2023	1 570 (Estimated)

- Solar energy usage has seen rapid growth, increasing from 724 TWh in 2019 to an estimated 1,570 TWh in 2023. This surge in solar energy generation reflects the global push toward renewable energy, especially in major markets like China, the European Union, and the United States.
- China played a leading role, contributing to over 60 % of the global solar capacity additions in 2023. Countries like India, Brazil, and Germany also saw significant solar installations in recent years(Our World in Data)(PV Tech)(IEA)(Ember). This rapid growth in solar power is part of a broader global shift towards renewable energy, driven by lower costs, supportive policies, and advancements in solar technology.

1.2.3 Solar Power in Standalone and Grid-Connected Systems

Solar power systems are used in two primary configurations: standalone (off-grid) and grid-connected systems. Each has its own advantages, applications, and operational characteristics. Here's an overview of both types:

1.2.3.1 Standalone Solar Power Systems (Off-Grid Systems)

Standalone systems, also known as off-grid systems, are independent from the utility grid and rely solely on the solar energy they generate. These systems are typically used in remote locations where grid access is unavailable or unreliable, such as rural areas, islands, or isolated homes.

Components:

- **Solar Panels:** Generate electricity from sunlight.
- **Battery Storage:** Stores excess energy generated during the day for use during nighttime or cloudy periods.
- **Charge Controller:** Regulates the flow of electricity to the batteries, preventing overcharging or deep discharge.
- **Inverter:** Converts direct current (DC) generated by solar panels into alternating current (AC) for use in typical household appliances.

- **Backup Generator (optional):** A diesel or other fuel-based generator may be included for extended periods of low sunlight.

Advantages:

- **Independence:** Fully independent of the grid, making it suitable for remote locations.
- **Energy Security:** Provides electricity in areas where the grid is unreliable or nonexistent.
- **Customizable:** Can be designed according to the specific energy needs of the user.

Challenges:

- **High Initial Cost:** Requires significant investment in batteries and backup systems.
- **Energy Storage Limitations:** Battery systems need to be well-sized and managed, which can increase costs.
- **Energy Management:** Users need to manage energy consumption carefully, especially during low sunlight periods.

Use Cases:

- Remote homes, cabins, or farms
- Telecommunications towers
- Rural healthcare centers
- Island or isolated communities

1.2.4 Grid-Connected Solar Power Systems

Grid-connected solar power systems are tied to the utility grid, allowing users to draw power from the grid when solar energy is insufficient (e.g., at night or during cloudy days) and feed excess energy back into the grid during periods of high solar generation. This system is commonly used in residential, commercial, and industrial applications.

Components:

- **Solar Panels:** Generate electricity from sunlight.
- **Inverter:** Converts DC power from solar panels into AC power for grid compatibility.
- **Net Metering/Bi-Directional Meter:** Measures the electricity supplied to and drawn from the grid, enabling the user to sell excess energy back to the grid.
- **Grid Connection:** Acts as a backup power source when solar power is insufficient.

Advantages:

- **No Need for Battery Storage:** Since the system is connected to the grid, excess power is fed into the grid, and the grid acts as a backup.
- **Cost Savings:** Users can significantly reduce electricity bills and potentially earn money through net metering programs.

- **Low Maintenance:** Batteries are not required, reducing maintenance and cost.

Challenges:

- **Dependence on the Grid:** During grid outages, most grid-tied systems shut down to prevent back-feeding electricity into the grid for safety reasons.
- **No Power During Outages:** Without a backup system like a battery or generator, the system does not provide power during grid outages, even if it is sunny.

Use Cases:

- Residential homes in urban and suburban areas
- Commercial buildings and factories
- Large-scale solar farms feeding electricity into the grid

Both standalone and grid-connected solar systems have their specific applications and benefits. Standalone systems are ideal for remote areas or where energy independence is crucial, while grid-connected systems are more suited for urban and commercial environments where the grid can supplement solar power. The choice between the two depends on energy needs, geographic location, and cost considerations.

1.2.5 Advantages and Challenges of Solar Energy

1.2.6 Advantages

1. **Renewable and Sustainable:** Solar energy is a renewable resource that can be harnessed in virtually all areas of the world and will never run out, making it an essential part of the global push for sustainable energy. Unlike fossil fuels, solar power does not deplete natural resources [62].
2. **Reduces Electricity Bills:** Installing solar panels allows individuals and businesses to generate their own electricity, reducing dependence on the grid and lowering electricity bills. In grid-connected systems, excess energy can be sold back to the grid through net metering, further reducing costs.
3. **Low Operating Costs:** Once installed, solar power systems require minimal maintenance. There are no fuel costs, and maintenance is limited mainly to cleaning panels and occasional system checks. Solar panels have long lifespans, often lasting 25 to 30 years.
4. **Reduces Carbon Footprint:** Solar power is a clean energy source, producing no direct greenhouse gas emissions during operation. This makes it an ideal solution for mitigating climate change and reducing air pollution.
5. **Energy Independence:** Solar energy provides countries, businesses, and individuals with greater energy security. It reduces reliance on imported energy and fossil fuels, which are subject to price fluctuations and geopolitical tensions.

1.2.6.1 Challenges of Solar Energy

1. **High Initial Costs:** The upfront cost of purchasing and installing solar panels, inverters, and batteries can be high, making it a significant financial investment. However, costs have been declining, and financial incentives like tax credits can mitigate some of this burden.
2. **Intermittent Energy Source:** Solar energy is weather-dependent and produces less energy on cloudy days or at night, requiring storage solutions (batteries) or backup systems (like grid power or generators) to ensure a consistent energy supply.
3. **Energy Storage:** Efficient and cost-effective energy storage is a major challenge. Batteries are often expensive, and they need to be large enough to store excess solar energy for use when sunlight is unavailable. Technological advancements are improving this, but it remains a barrier.
4. **Space Requirements:** Solar panels require large spaces to produce significant amounts of energy. For individual homes, roof space is often sufficient, but for larger installations (commercial or utility-scale solar farms), acquiring enough land can be a challenge, especially in urban areas.
5. **Material Scarcity and Environmental Impact:** Although solar energy is clean, the production of solar panels involves mining raw materials like silicon and rare earth metals, which can have environmental impacts. Additionally, disposing of old or damaged panels at the end of their life cycle poses another environmental challenge [134].

Solar energy, harnessed through both standalone and grid-connected systems, has emerged as a vital component of the global shift toward renewable and sustainable energy sources. Its advantages are numerous: it is a renewable resource that reduces electricity bills, requires minimal maintenance, lowers carbon footprints, and promotes energy independence. These benefits are driving its rapid adoption worldwide, as shown by the global increase in solar energy usage over the past five years, with substantial contributions from countries like China, the U.S., and India.

However, challenges still exist, particularly the high initial installation costs, the intermittency of solar energy, and the need for advanced energy storage solutions. While solar power is weather-dependent and requires large spaces for large-scale installations, continued technological advancements and falling solar costs make these obstacles more manageable. Additionally, the environmental impact of producing solar panels and dealing with material scarcity must be addressed to ensure the sustainability of the entire solar power lifecycle.

Overall, solar energy presents a critical solution to both the energy and environmental crises, contributing significantly to reducing global dependence on fossil fuels and helping countries meet climate change targets. As technological improvements continue to lower costs and enhance efficiency, the future of solar energy looks increasingly promising. Its widespread adoption is expected to further accelerate, contributing to a cleaner, more resilient global energy system.

1.3 Wind Energy Systems

Wind energy systems convert the kinetic energy from wind into electrical power through the use of wind turbines. Wind energy is one of the most rapidly growing renewable energy

sources and is critical in the global transition towards a more sustainable energy system. Below is a comprehensive overview of wind energy systems, including types, components, advantages, and challenges [32].

1.3.1 Types of Wind Energy Systems

1. **Onshore Wind Energy Systems:**
   - Onshore systems are located on land and are the most common type of wind energy systems. They tend to have lower installation and maintenance costs compared to offshore systems due to easier access.
   - **Advantages:** Lower cost of installation, easier maintenance, access to the grid.
   - **Challenges:** Visual and noise pollution, land usage conflicts, and less consistent wind speeds.
2. **Offshore Wind Energy Systems:**
   - Offshore wind farms are built in bodies of water, typically in the ocean. These systems harness stronger and more consistent winds but are more expensive to install and maintain due to the complex logistics of operating at sea [124].
   - **Advantages:** Higher and more consistent wind speeds, no land usage conflict.
   - **Challenges:** High installation and maintenance costs, more complex infrastructure.

1.3.2 Key Components of Wind Energy Systems

1. **Wind Turbines:**
   - **Rotor Blades:** Capture wind energy and convert it into rotational motion.
   - **Nacelle:** Houses components such as the gearbox and generator, converting mechanical energy into electrical energy.
   - **Tower:** Supports the turbine at a height where it can capture higher wind speeds.
2. **Gearbox:** Increases the rotation speed from the rotor blades to match the operational speed of the generator.
3. **Generator:** Converts mechanical energy from the rotating blades into electrical energy.
4. **Controller and Power Electronics:** Regulates the system to ensure safe and optimal operation, connects the system to the grid, and manages power output.

1.3.3 How Wind Energy Systems Work

Wind turbines operate on a simple principle: when wind blows over the blades, they turn, which spins the shaft connected to a generator, creating electricity. The amount of energy produced depends on wind speed, the turbine's height, and blade size.

1. **Wind Capture:** Wind causes the rotor blades to spin, converting wind energy into rotational energy.
2. **Energy Conversion:** The rotational energy is transferred through the gearbox to the generator, where it is converted into electricity.

3. **Electricity Transmission:** The generated electricity is sent to the grid for distribution or stored in batteries for later use.

1.3.4 Advantages of Wind Energy Systems

1. **Renewable and Sustainable:** Wind is a plentiful and inexhaustible resource, making wind energy a reliable renewable energy source.
2. **Reduces Carbon Emissions:** Wind energy produces no greenhouse gas emissions during operation, making it an environmentally friendly alternative to fossil fuels.
3. **Scalability:** Wind farms can be scaled from small residential applications to large utility-scale installations, making wind energy adaptable to different needs.
4. **Job Creation:** The wind energy industry creates jobs in manufacturing, installation, maintenance, and other related fields, boosting local economies.
5. **Energy Independence:** Wind energy can reduce dependence on imported fuels and improve a country's energy security.

1.3.5 Challenges of Wind Energy Systems

1. **Intermittency:** Wind energy production is not constant, as wind speeds can fluctuate, making it less reliable without adequate storage or backup systems.
2. **Land and Environmental Impact:** Onshore wind farms can face opposition due to their impact on local landscapes, wildlife, and noise concerns.
3. **High Initial Costs:** Wind turbines, especially offshore, require significant upfront capital investment for installation and infrastructure, although operational costs are low.
4. **Grid Integration:** Integrating variable wind power into the grid requires improvements in grid flexibility, energy storage solutions, and grid management systems.
5. **Maintenance and Durability:** Offshore wind turbines are exposed to harsh marine conditions, leading to higher maintenance needs and shorter lifespans compared to onshore systems.

1.3.6 Wind Energy Systems

Wind energy is the process of converting kinetic energy from the wind into electrical power using wind turbines. This form of renewable energy harnesses the natural movement of air caused by atmospheric pressure differences to produce clean, sustainable electricity [111].

Globally, wind energy holds immense potential, as it is one of the most abundant renewable resources available. Regions with strong and consistent wind speeds, both onshore and offshore, have the greatest potential to generate significant portions of their energy needs through wind power. Factors influencing this potential include:

- Speed and consistency of wind
- Geographical location

- Advancements in turbine technology

Wind energy provides numerous benefits:

- Renewable and sustainable energy source
- Reduces dependency on fossil fuels
- Lowers greenhouse gas emissions
- Enhances energy security by diversifying energy sources

However, challenges such as intermittency, land requirements, wildlife impact, and technological and financial barriers (especially in offshore wind development) must be addressed to fully harness its potential.

1.3.6.1 Wind Turbine Technology

Wind turbine technology refers to the advanced machinery and systems designed to convert the kinetic energy of wind into usable electrical energy. A wind turbine typically consists of three main components:

- **Rotor Blades**: Capture wind energy and convert it into rotational motion.
- **Shaft**: Transfers rotational energy from the blades to the generator.
- **Generator**: Converts mechanical energy into electrical energy.

Modern wind turbines incorporate control systems such as:

- **Pitch Control**: Adjusts blade angles to optimize energy capture.
- **Yaw Control**: Rotates the turbine to face the wind for maximum efficiency.

Advancements in blade design and materials have led to more efficient energy capture, particularly with the development of longer and more aerodynamic blades. Offshore wind turbines, typically larger than onshore turbines, take advantage of stronger and more consistent wind speeds but face higher installation and maintenance costs.

1.3.6.2 Types of Wind Turbines

Wind turbines are categorized into two main types based on the orientation of their rotor axis relative to the ground:

1.3.6.2.1 Horizontal-Axis Wind Turbines (HAWT)

- Most commonly used in large-scale wind farms.
- Rotor shaft is positioned horizontally, parallel to the ground.
- Blades rotate perpendicular to the wind direction.
- Equipped with a yaw mechanism to align with the wind direction.
- High efficiency and scalability, suitable for both onshore and offshore installations.

1.3.6.2.2 Vertical-Axis Wind Turbines (VAWT)

- Rotor shaft is oriented vertically, allowing the turbine to capture wind from any direction.
- No need for a yaw mechanism, making them suitable for urban environments.
- Two common subtypes:
  - **Darrieus Turbine**: Features curved blades for better aerodynamic performance.
  - **Savonius Turbine**: Uses a rotating drum-like structure for simpler operation.
- Generally less efficient than HAWTS but require lower maintenance.

Both HAWTs and VAWTs have distinct advantages and limitations, with HAWTs being the preferred choice for large-scale energy production, while VAWTs are useful for smaller, decentralized applications, particularly in areas with limited space or inconsistent wind directions.

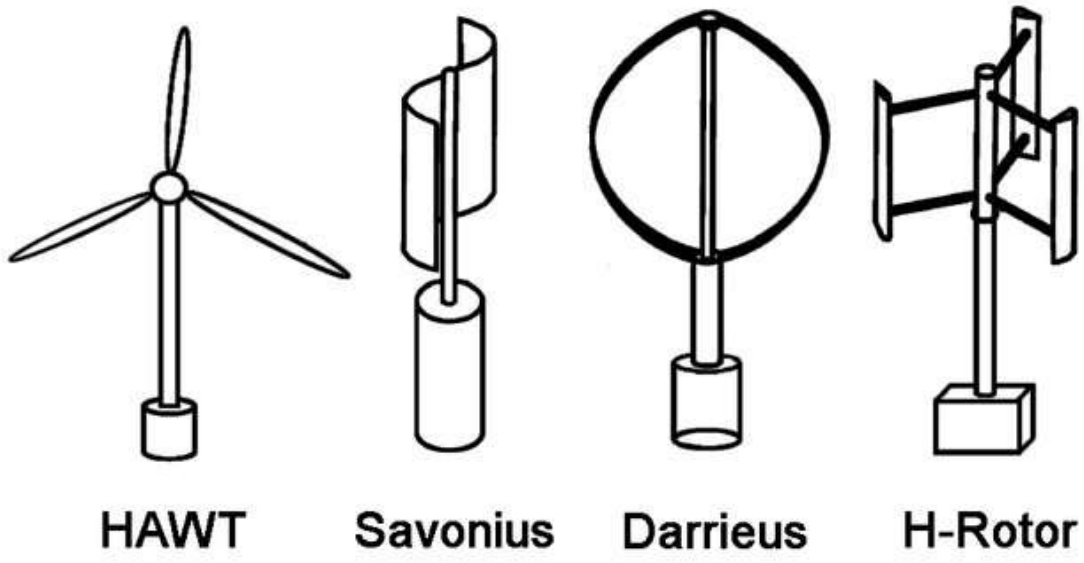


Figure 1.6: Types of Wind Turbines

1.3.6.3 Working Principle of Wind Energy Systems

The working principle of wind energy systems is based on the conversion of kinetic energy from the wind into mechanical energy, which is then transformed into electrical energy. This process takes place through a series of well-coordinated steps involving key components such as rotor blades, shafts, and generators.

1. **Wind Capture and Rotor Blade Movement:** As wind flows over the rotor blades of a wind turbine, it creates a pressure difference that causes the blades to rotate. The aerodynamic design of the blades allows them to harness the maximum amount of wind energy. The rotor blades are connected to a central hub, which in turn is attached to a low-speed shaft.

2. **Mechanical Energy Generation:** As the blades rotate, the low-speed shaft turns. This rotation generates mechanical energy. The speed of this shaft is generally low (around 30 to 60 rotations per minute for large turbines), which is insufficient for generating electricity.

3. **Speed Increase and Energy Transmission:** The low-speed shaft is connected to a gearbox, which increases the rotational speed of the shaft significantly. The high-speed shaft, which comes out of the gearbox, rotates at about 1,000 to 1,500 rotations per minute, making it suitable for driving the generator.

4. **Electricity Generation:** The high-speed shaft is connected to a generator, where the mechanical energy from the rotating shaft is converted into electrical energy. Inside the generator, the motion of the shaft drives the movement of magnetic fields, which induces an electrical current. The generated electricity is typically alternating current (AC), which is the standard form for grid distribution.

5. **Power Transmission and Grid Integration:** The electricity produced by the generator is sent to a transformer, where it is stepped up to a higher voltage for transmission over long distances. From there, the electricity is transmitted via power lines to the grid, where it is distributed to consumers. In off-grid applications, the power can be stored in batteries or used directly to meet energy demands.

Wind energy systems operate based on this principle, capturing wind energy efficiently and transforming it into usable electricity. The overall efficiency of the system depends on factors such as wind speed, turbine design, and the technological advancements in the components used in the energy conversion process.

1.3.7 Wind Power in Standalone and Grid-Connected Systems

1.3.7.1 Standalone Systems

Standalone wind power systems operate independently from the main power grid. These systems are typically used in remote locations where grid access is either unavailable or economically unfeasible. Standalone wind systems can be designed for small-scale applications, such as powering a household or a remote village, or for larger operations, such as providing energy for off-grid industrial applications.

Standalone systems are often combined with energy storage solutions, such as batteries or supercapacitors, to manage power fluctuations due to the variable nature of wind energy. Since wind speed and availability can fluctuate, storage is crucial to ensure a stable energy supply during periods of low wind.

Standalone wind systems are ideal for:

- Rural electrification
- Remote telecommunications stations
- Agricultural operations
- Small businesses or homes in remote areas

Key Features of Standalone Systems:

1. **Autonomy:** They operate independently of the grid, relying solely on wind power and storage systems.
2. **Energy Storage:** The inclusion of batteries or other energy storage devices helps balance the intermittency of wind power.
3. **Inverters:** Inverters are necessary to convert the generated DC power from the wind turbine to AC power for use in typical household or industrial applications.
4. **Cost:** Initial costs are relatively high due to the need for storage systems, but they offer long-term savings by eliminating reliance on grid power.

Challenges:

- The variability of wind power can lead to supply disruptions if storage systems are insufficient.
- Maintenance in remote locations can be costly and time-consuming.

1.3.7.2 Grid-Connected Systems

Grid-connected wind power systems are designed to feed power directly into the main electrical grid. These systems are widely used in both small-scale residential applications and large-scale commercial wind farms. In grid-connected systems, power generated by the wind turbines is used by the grid when available, and any excess power can be sold back to the utility company, providing an additional income stream.

Grid-connected wind systems help to diversify the energy mix, reduce reliance on fossil fuels, and contribute to a cleaner energy grid. Unlike standalone systems, grid-connected systems do not require energy storage, as the grid serves as a backup when wind power is insufficient.

Key Features of Grid-Connected Systems:

1. **Grid Integration:** Wind turbines are connected to the main grid, allowing for power to be supplied directly to consumers or sold back to utilities.
2. **No Need for Storage:** Since the grid acts as a backup, energy storage is not typically required.
3. **Net Metering:** Excess power can be sold to the grid, creating opportunities for financial returns.
4. **Scalability:** These systems can range from small residential setups to large-scale wind farms supplying significant amounts of electricity to the grid.

Challenges:

- Grid integration requires careful consideration of power quality and frequency stability, as the variability of wind can affect overall grid performance.
- Regulatory frameworks and policies, such as feed-in tariffs and grid connection requirements, vary between regions and can affect system viability.

1.3.7.3 Comparison Between Standalone and Grid-Connected Systems

- **Reliability:** Grid-connected systems are generally more reliable because they have the grid as a backup. Standalone systems require energy storage and careful management to ensure a continuous power supply.
- **Cost:** Standalone systems tend to be more expensive due to the need for energy storage. However, grid-connected systems may require additional investment in infrastructure to connect to the grid.
- **Energy Independence:** Standalone systems offer complete energy independence, while grid-connected systems still rely on the grid as a backup.

Both standalone and grid-connected wind power systems play a crucial role in the global energy landscape. Standalone systems are ideal for remote or isolated areas, while grid-connected systems offer a scalable solution for integrating wind energy into existing power networks. The choice between these systems depends on factors such as location, grid accessibility, and energy demand.

1.4 Hybrid Solar and Wind Energy Systems

1.4.1 Overview

Hybrid solar and wind energy systems combine two renewable energy sources—solar photovoltaic (PV) panels and wind turbines—to provide a more reliable and continuous energy supply [26]. By harnessing both solar and wind energy, these systems can take advantage of different weather conditions, ensuring power generation even when one resource is limited. Hybrid systems can be used in both standalone (off-grid) and grid-connected configurations.

The complementarity of solar and wind resources makes hybrid systems more efficient, especially in areas where both sunlight and wind are available in different seasons or times of the day [26]. For example, wind energy tends to be more abundant at night and during winter months, while solar energy is most effective during the day and in summer. This balance helps smooth out power generation fluctuations and improves the overall performance and reliability of the system.

1.4.2 Concept of Hybrid Energy Systems

The concept of hybrid energy systems revolves around the integration of multiple energy sources to create a more reliable, efficient, and sustainable power supply. Typically, these systems combine renewable energy sources, such as solar, wind, or hydroelectric power, with each other or with conventional energy sources like diesel generators. By incorporating a variety of energy resources, hybrid systems can mitigate the intermittency issues that often affect standalone renewable energy systems and provide a more consistent energy output.

At the core of a hybrid energy system is the idea of complementarity between different energy sources. For example, solar and wind energy are often used together because of their complementary nature—solar power is typically most abundant during the day, while wind energy can be more prevalent at night or during cooler seasons. By combining these sources, hybrid systems can provide electricity around the clock, reducing the need for large-scale energy storage and minimizing periods of low energy generation.

Hybrid energy systems can be deployed in various configurations depending on the specific needs and available resources of a location [143]. Off-grid hybrid systems are widely used in remote areas where grid access is limited or unavailable. These systems often incorporate renewable energy sources, energy storage (such as batteries), and sometimes conventional backup generators. The primary advantage of such a setup is energy autonomy, ensuring that remote communities or industrial sites can maintain a stable power supply without relying on the grid.

Grid-connected hybrid energy systems operate by feeding power from renewable sources into the grid while drawing on grid electricity when necessary. These systems reduce dependency on fossil fuels and allow users to sell excess energy back to the grid, improving energy efficiency and providing financial incentives. Grid-connected hybrids may or may not include energy storage, depending on the design and objectives of the system.

One of the significant benefits of hybrid energy systems is their flexibility and scalability. They can be tailored to meet the specific energy demands of various applications, from small residential setups to large-scale industrial installations. The integration of multiple energy sources not only enhances reliability but also optimizes energy production by diversifying the power generation mix. In some cases, hybrid systems also include smart controllers to ensure efficient management of power flow between sources, energy storage, and the grid.

Despite their numerous advantages, hybrid energy systems also come with challenges. They require a higher initial capital investment due to the complexity of integrating different technologies and managing energy flow. Furthermore, the effectiveness of these systems depends on the local availability of renewable resources, such as sunlight or wind, as well as the technical infrastructure for grid integration.

In summary, the concept of hybrid energy systems presents a robust solution to the challenges of renewable energy by combining multiple sources to enhance reliability, reduce intermittency, and optimize energy efficiency. These systems play a critical role in advancing the transition to cleaner energy, offering flexibility for both off-grid and grid-connected applications while contributing to long-term sustainability. Figure **??** illustrates the main components of Hybrid (wind and solar) system

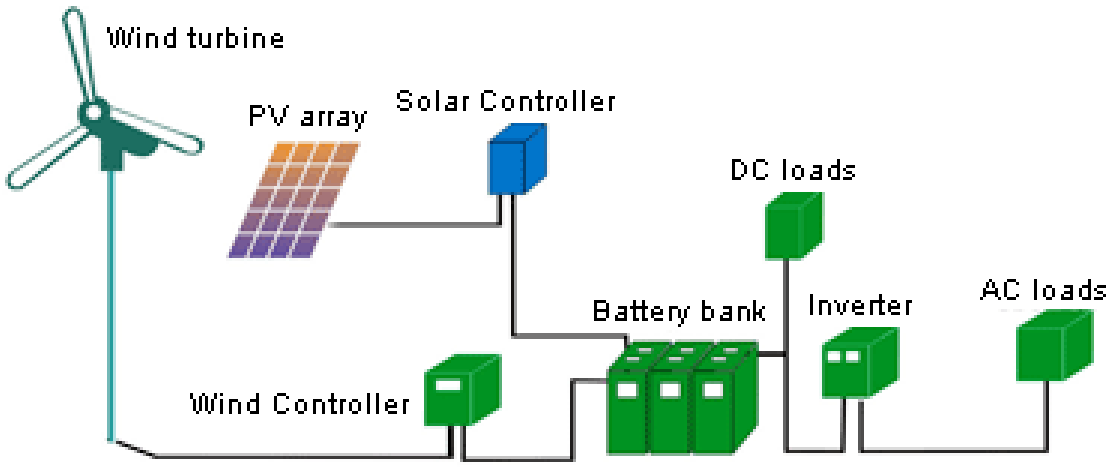


Figure 1.7: Main Components of a hybrid (wind and solar) System

1.4.3 Synergy Between Solar and Wind Energy

The synergy between solar and wind energy arises from their complementary characteristics, which make them ideal partners in hybrid energy systems. Solar and wind resources often exhibit opposite patterns in availability, meaning that when one resource is less available, the other may be more abundant. This complementary nature allows hybrid systems combining solar and wind energy to provide a more reliable and consistent energy supply than systems relying on either source alone.

Temporal Complementarity: Solar energy generation peaks during daylight hours, especially on clear, sunny days. However, solar energy is unavailable at night and may be significantly reduced on cloudy days or during winter months. Wind energy, on the other hand, tends to be more abundant during the night, in colder seasons, or in windy weather conditions. This temporal complementarity allows solar and wind hybrid systems to generate power more continuously throughout the day and across different seasons.

For example, in many locations, wind speeds are higher during the night when solar energy is unavailable, and solar generation peaks during the day when wind speeds may be lower. By capturing both resources, a hybrid system can smooth out the daily and seasonal fluctuations in energy generation, reducing the need for large energy storage systems and increasing overall efficiency.

Geographical Complementarity: The geographical distribution of solar and wind energy resources also enhances their synergy. In some regions, solar energy may be more plentiful in inland or desert areas, while wind energy is more abundant in coastal or hilly regions. A hybrid system can be designed to take advantage of these geographical differences, with solar installations in areas with high solar insolation and wind turbines in locations with strong, consistent winds. This spatial complementarity ensures a more diverse and distributed generation of renewable energy.

Reduced Storage Needs and Grid Stability: By combining solar and wind energy, hybrid systems can reduce the dependency on large-scale energy storage, which is often necessary to compensate for the variability of standalone renewable energy sources. Since solar and wind tend to complement each other, energy storage systems can be smaller and less costly, as they only need to store energy for shorter periods when both resources are unavailable.

This synergy also enhances grid stability, especially in grid-connected systems. The fluctuating nature of renewable energy sources like solar and wind can sometimes cause instability in power grids. However, by combining the two sources, hybrid systems can provide a more stable and predictable power output, helping to balance supply and demand more effectively.

Economic and Environmental Benefits: The synergy between solar and wind also leads to economic and environmental benefits. By generating more continuous power, hybrid systems can reduce reliance on fossil fuel-based backup generators, which are often used to compensate for the variability of renewable energy. This not only lowers operational costs but also reduces greenhouse gas emissions and the environmental impact of power generation.

In conclusion, the synergy between solar and wind energy significantly enhances the reliability, efficiency, and sustainability of hybrid energy systems. By complementing each other's availability patterns, these two renewable resources create a more balanced and consistent power supply, which reduces storage requirements, improves grid stability, and contributes to cost savings and environmental sustainability.

1.4.3.1 Complementary Nature of Solar and Wind Resources

The complementary nature of solar and wind resources forms the foundation for hybrid energy systems. Solar energy is most abundant during daylight hours, particularly in clear and sunny conditions, and peaks in the summer. Conversely, wind energy tends to be more prevalent at night, during cloudy or stormy weather, and in colder months, especially in coastal or mountainous regions. This difference in generation patterns allows solar and wind energy to compensate for each other's variability, ensuring more consistent power generation across various conditions. By harnessing these complementary characteristics, hybrid systems can provide a more reliable energy supply, reducing the intermittency challenges often faced by standalone renewable energy systems.

1.4.3.2 Balancing Energy Generation: Day-Night and Seasonal Variations

A significant advantage of hybrid solar-wind systems is their ability to balance energy generation across day-night cycles and seasonal variations. Solar panels generate energy when the sun is shining, but their output drops to zero at night. In contrast, wind turbines often produce more energy at night or during seasons with stronger winds. This day-night variation ensures that power generation continues when either resource alone might fail to meet demand. Similarly, solar power peaks in the summer, while wind generation can increase in the winter months. The combination of these two sources thus helps smooth out energy production over time, providing a more stable and predictable energy supply.

1.4.4 Advantages of Hybrid Solar-Wind Systems

1. **Improved Reliability and Stability:** One of the primary advantages of hybrid solar-wind systems is enhanced reliability. By combining two renewable sources, the system can generate electricity more consistently, even when one resource is unavailable. This leads to greater energy security, especially in off-grid applications, and reduces the risk of power shortages.

2. **Reduced Need for Energy Storage:** Since solar and wind resources often peak at different times, hybrid systems can significantly reduce the reliance on large and expensive energy storage systems. With more continuous energy generation, storage requirements are limited to bridging shorter periods of low resource availability, thus lowering overall system costs.

3. **Cost Savings:** Over time, hybrid solar-wind systems can lead to significant cost savings. The combination of complementary resources minimizes the need for backup systems, reduces fuel costs in remote locations, and allows for more efficient use of energy infrastructure. Additionally, hybrid systems in grid-connected setups can sell excess energy back to the grid, providing a financial return on investment.

4. **Environmental Benefits:** Hybrid solar-wind systems contribute to reduced greenhouse gas emissions by relying on clean, renewable energy sources. The reduced need for backup generators, which often rely on fossil fuels, further lowers carbon emissions, making hybrid systems a more environmentally sustainable option.

5. **Scalability and Flexibility:** Hybrid systems are highly adaptable and can be scaled to meet different energy demands, from small residential setups to large industrial or

utility-scale applications. They can also be tailored to the specific resource availability of a location, optimizing performance based on local solar and wind conditions.

1.4.5 Challenges in Hybrid Energy System Design and Integration

1. **High Initial Costs:** The upfront investment required for hybrid systems can be significant, as they involve the integration of two renewable energy technologies, energy storage, and advanced control systems. The costs of installation, maintenance, and energy management infrastructure can be higher than those for standalone systems.

2. **Complexity of System Design:** Designing a hybrid solar-wind system is more complex than designing a single-source system. The integration of solar panels, wind turbines, energy storage, and control units requires careful planning to ensure that all components work harmoniously. Additionally, the system must be able to handle variations in power output from both sources while maintaining efficiency.

3. **Location-Specific Effectiveness:** The performance of hybrid solar-wind systems is highly dependent on the geographical location and availability of both solar and wind resources. In some regions, one resource may dominate, limiting the benefits of the hybrid approach. For example, areas with low wind speeds may not fully capitalize on the wind energy component, reducing overall efficiency.

4. **Energy Management and Control:** Managing the flow of energy between solar, wind, storage, and the grid requires sophisticated control systems. Ensuring that energy is efficiently distributed to meet demand while minimizing losses and optimizing storage use is a technical challenge. This complexity can lead to higher operation and maintenance costs over time.

5. **Grid Integration:** In grid-connected hybrid systems, integrating intermittent renewable sources like solar and wind can pose challenges for grid stability. Variations in power output due to changing weather conditions can cause fluctuations in energy supply, requiring grid operators to balance loads carefully. Advanced grid infrastructure, smart inverters, and energy management systems are often needed to ensure smooth integration.

In conclusion, while hybrid solar-wind systems offer significant advantages in terms of reliability, efficiency, and sustainability, they also present challenges that need to be carefully addressed during the design and integration process. Overcoming these challenges is crucial to fully realizing the potential of hybrid energy systems in a diverse range of applications.

1.5 Advanced Control Strategies for Hybrid Energy Systems

Advanced control strategies are essential for optimizing the performance and efficiency of hybrid energy systems. These strategies involve sophisticated algorithms and techniques designed to enhance energy generation, manage resources effectively, and ensure stable power delivery. By employing advanced control methods, hybrid systems can better adapt to changing environmental conditions, maximize renewable energy utilization, and minimize operational costs.

Table 1.2: Summary of Advanced Control Strategies for Hybrid Energy Systems [22]

Control Strategy	**Type**	**Main Features**	**Applications**	**Advantages**
Rule-Based Control	Conventional	Simple logic, if-then rules	Basic hybrid systems	Easy to implement, low computational demand
Fuzzy Logic Control (FLC)	Intelligent / Soft	Handles uncertainty, linguistic rules, no need for accurate models	PV-wind-diesel, microgrids	Robust to disturbances, suitable for nonlinear systems
Neural Network Control (ANN)	Intelligent / AI-Based	Learns from data, nonlinear approximation	MPPT, power management	Self-adaptive, high accuracy, predictive capability
Model Predictive Control (MPC)	Advanced / Model-Based	Optimizes control actions over time horizon using system model	Energy scheduling, grid integration	Optimal operation, handles constraints and multi-objective functions
M5-Tree-Based Control	AI / Data-Driven	Combines decision trees with regression, interpretable	MPPT, power flow control	Fast response, accurate decisions, explainable results
Genetic Algorithm (GA)	Evolutionary / Meta-heuristic	Global optimization, population-based search	Parameter tuning, optimization problems	Finds optimal solutions, flexible for complex systems
Particle Swarm Optimization (PSO)	Swarm Intelligence	Cooperative agents simulate social behavior	MPPT, storage management	Fast convergence, suitable for real-time implementation
Sliding Mode Control (SMC)	Robust / Nonlinear	High robustness to disturbances and uncertainties	Wind and PV converters	Precise control, robust to parameter variations
Hybrid Control Approaches	Combined Methods	Merging two or more strategies (e.g., ANN + FLC)	Complex hybrid energy systems	Balances accuracy, robustness, and flexibility
Reinforcement Learning (RL)	AI / Deep Learning	Learns optimal policy via trial and error	Autonomous energy management systems	Adaptive, learns in dynamic environments

1.5.1 Role of Maximum Power Point Tracking (MPPT) in Hybrid Systems

Maximum Power Point Tracking (MPPT) is a crucial technology in hybrid energy systems, particularly for solar power integration. MPPT algorithms optimize the power output from solar panels by continuously adjusting the electrical operating point of the modules. As solar irradiance and temperature fluctuate throughout the day, the optimal operating point changes. MPPT ensures that solar panels operate at their maximum power point, maximizing energy extraction and improving overall system efficiency.

In hybrid systems that combine solar and wind energy, MPPT is typically applied to both sources. For solar panels, MPPT controllers dynamically adjust the load to extract maximum power. In wind energy systems, similar algorithms optimize the turbine operation by adjusting blade pitch or rotor speed to capture the maximum available wind energy. By implementing MPPT in hybrid systems, operators can enhance energy generation, especially during variable weather conditions, leading to improved reliability and reduced reliance on backup power sources.

1.5.2 Energy Management Strategies in Hybrid Systems

Energy management strategies (EMS) play a vital role in optimizing the operation of hybrid energy systems. EMS involves the coordinated control and monitoring of different energy sources and storage components to ensure efficient energy utilization and grid stability. The primary objectives of EMS in hybrid systems include:

- **Load Forecasting:** Predicting energy demand based on historical data and real-time inputs helps in optimizing resource allocation and ensuring that energy supply meets demand.
- **Resource Scheduling:** EMS dynamically schedules the operation of solar, wind, and storage components to maximize energy production while minimizing costs. This includes deciding when to charge or discharge batteries and when to draw energy from the grid or renewable sources.
- **Demand Response:** Implementing demand response strategies allows operators to adjust energy consumption based on availability. This helps balance supply and demand, especially during peak periods or when renewable generation is low.
- **Optimization Algorithms:** Advanced optimization techniques, such as linear programming, genetic algorithms, or machine learning, can be employed to improve the overall efficiency and performance of hybrid systems by optimizing resource allocation and energy flow.

By effectively managing energy resources, EMS contributes to the overall stability and reliability of hybrid systems while reducing operational costs and environmental impact.

1.5.3 Importance of Power Electronics and Control for Hybrid Systems

Power electronics and control technologies are integral to the successful operation of hybrid energy systems. These technologies facilitate the conversion, control, and distribution of electrical energy from various sources to loads. The importance of power electronics in hybrid systems can be summarized as follows [60]:

- **Energy Conversion:** Power electronic devices, such as inverters, converters, and controllers, are essential for converting DC power generated by solar panels and batteries into AC power suitable for grid integration. This conversion is crucial for maintaining power quality and ensuring compatibility with the electrical grid.
- **Control Flexibility:** Advanced control strategies, enabled by power electronics, allow for precise regulation of power flow between different components in hybrid systems. This flexibility is vital for responding to varying energy generation and consumption patterns, ensuring optimal system performance.
- **Grid Synchronization:** Power electronics facilitate the synchronization of renewable energy sources with the grid, enabling efficient energy transfer and maintaining grid stability. This synchronization is essential for integrating intermittent renewable sources and ensuring a reliable power supply.
- **Protection and Fault Management:** Power electronic devices also play a critical role in protecting hybrid systems from faults or disturbances. They enable rapid response to abnormal conditions, ensuring the safety and reliability of the system.

1.6 Grid Integration of Hybrid Solar-Wind Systems

The integration of hybrid solar-wind systems into the electrical grid represents a significant advancement in renewable energy technology. These systems harness the complementary strengths of solar and wind energy, providing a more stable and reliable power supply. However, successful integration requires careful consideration of various technical, regulatory, and economic factors.

1.6.1 Technical Considerations for Grid Integration

Integrating hybrid solar-wind systems into the grid involves several technical considerations, including [74]:

- **Interconnection Standards:** Each region has specific interconnection standards that dictate how renewable energy systems can connect to the grid. Adhering to these standards ensures that the hybrid system operates safely and effectively while meeting grid requirements.
- **Power Quality Management:** The variability in power generation from solar and wind sources can lead to fluctuations in voltage and frequency. Power quality management techniques, including advanced inverters and energy management systems, are essential for ensuring that the output from hybrid systems meets the required quality standards for grid integration.
- **Grid Stability and Reliability:** Hybrid systems must contribute to grid stability by providing ancillary services such as frequency regulation and voltage support. This may involve implementing advanced control strategies that allow the hybrid system to respond quickly to changes in grid conditions.
- **Energy Storage Integration:** Incorporating energy storage solutions, such as batteries, is critical for managing the intermittent nature of solar and wind energy. Storage

systems can store excess energy generated during peak production times and release it during low production periods, thus helping to balance supply and demand.

- **Communication and Monitoring Systems:** Effective communication and monitoring systems are vital for real-time data exchange between hybrid systems and grid operators. These systems enable better coordination of energy production and consumption, facilitating efficient grid management [108].

Table 1.3: Technical Considerations for Grid Integration of Hybrid Solar and Wind Energy Systems [85]

Technical Aspect	**Description**	**Challenges**	**Solutions / Techniques**
Power Quality	Ensures voltage/frequency stability, reduces harmonics	Voltage sags, swells, flickers, harmonics	Filters, FACTS devices, advanced converters
Voltage and Frequency Control	Maintains grid standards under dynamic inputs	Intermittency of wind/solar, grid code violations	Smart inverters, droop control, synchronization schemes
Grid Code Compliance	Fulfills utility and regional grid interconnection rules	Diverse codes for different regions	Real-time monitoring, adaptive controllers
Protection Schemes	Ensures safety of system and personnel	Fault detection in distributed systems	Adaptive relays, islanding detection methods
Energy Storage Integration	Compensates for variability, enhances reliability	High cost, sizing complexity	Battery banks, supercapacitors, hybrid storage systems
Power Flow Management	Balances supply-demand between RES and grid	Bi-directional flow, dynamic line loading	Power electronic interfaces, optimal load dispatch
Communication and Control	Enables real-time decision-making and coordination	Latency, cybersecurity, interoperability issues	SCADA, IoT-based systems, secure protocols
Islanding and Resynchronization	Detects grid disconnection and safely resynchronizes	Delays in detection, reconnection issues	Passive/active detection methods, PLLs
Forecasting and Scheduling	Predicts generation and plans accordingly	Forecast errors, uncertain weather patterns	AI/ML-based forecasting, hybrid models
Economic Dispatch	Optimizes cost-effective energy distribution	Varying cost profiles, uncertainty	Linear programming, market-based dispatch algorithms
Reactive Power Management	Regulates voltage and supports grid stability	Fluctuating loads, inverter limits	Dynamic VAR compensation, smart inverters
Synchronization	Aligns phase and frequency with grid	Inaccurate tracking, unstable transitions	Phase-locked loops (PLLs), digital control schemes
Load Following Capability	Matches power generation with demand changes	Delayed response, overshoot/undershoot	Fast-acting control systems, demand-side management
Resilience to Grid Faults	Maintains operation during grid disturbances	Voltage dips, frequency instability	Low-voltage ride-through (LVRT), fault-tolerant control
Standards and Certification	Ensures safety, quality, and interoperability	Non-uniform standards across manufacturers	Compliance testing, IEC/IEEE/ISO certification

1.6.2 Regulatory and Economic Aspects

Successful integration of hybrid solar-wind systems also depends on navigating various regulatory and economic factors:

- **Regulatory Frameworks:** Clear regulatory frameworks are essential for guiding the development and integration of hybrid renewable energy systems. This includes policies that promote renewable energy use, set interconnection standards, and establish incentives for hybrid system implementation.
- **Incentives and Subsidies:** Financial incentives, such as tax credits, grants, and feed-in tariffs, can encourage investment in hybrid solar-wind systems. These incentives help reduce the upfront costs and improve the economic viability of integrating renewable energy into the grid.
- **Cost-Benefit Analysis:** Conducting a comprehensive cost-benefit analysis is crucial for assessing the economic feasibility of hybrid systems. This analysis should consider capital costs, operational expenses, potential savings from reduced fossil fuel use, and revenues from selling excess energy back to the grid.
- **Market Participation:** Hybrid systems can participate in energy markets by providing ancillary services, such as frequency regulation or demand response. Market participation creates additional revenue streams and supports the overall stability of the power grid.
- **Stakeholder Engagement:** Engaging with stakeholders, including utility companies, regulatory bodies, and local communities, is essential for addressing concerns and ensuring a smooth integration process. Collaborative efforts can lead to more robust policies and frameworks that support hybrid renewable energy systems.

In conclusion, the grid integration of hybrid solar-wind systems involves complex technical, regulatory, and economic considerations. By addressing these challenges, stakeholders can harness the full potential of hybrid systems, contributing to a cleaner, more resilient, and sustainable energy future. The successful integration of these systems into the grid not only enhances energy security but also promotes the transition to a low-carbon energy landscape.

1.7 Conclusion

Hybrid Renewable Energy Systems (HRES) represent a transformative approach to addressing the global energy crisis, offering a sustainable and reliable alternative to conventional fossil fuel-based energy production. By integrating solar and wind energy, HRES take advantage of the complementary nature of these renewable sources, reducing the intermittency and enhancing the stability of energy generation. This capability is particularly critical in regions with fluctuating energy demand and supply, where a single renewable source may not provide the consistency required for stable energy distribution.

One of the key advantages of HRES is its ability to enhance energy security and independence. By reducing reliance on imported fossil fuels and harnessing locally available renewable resources, these systems empower communities and countries to take control of their energy future. Additionally, HRES contribute to environmental sustainability by significantly reducing greenhouse gas emissions, helping to combat climate change and mitigate

its impacts. As the global community strives to meet ambitious climate targets, such as those set forth in the Paris Agreement, the widespread adoption of HRES will be essential in reducing carbon footprints and promoting green energy transitions.

Moreover, HRES are instrumental in improving energy access, particularly in remote or off-grid areas where traditional grid infrastructure is lacking. In such regions, the integration of solar, wind, and energy storage systems can provide a consistent and reliable power supply, fostering social and economic development. By enabling energy independence and reducing energy poverty, HRES play a vital role in advancing the United Nations' Sustainable Development Goals (SDGs), particularly Goal 7, which seeks to ensure access to affordable, reliable, sustainable, and modern energy for all.

However, the implementation of HRES is not without challenges. The complexity of integrating multiple renewable sources, the need for advanced energy management systems, and the initial capital investment required for setting up hybrid systems can be significant barriers to widespread adoption. Additionally, the efficiency of HRES depends on factors such as geographic location, local weather patterns, and the availability of renewable resources, making careful planning and system design essential for maximizing their effectiveness. Continued research and development are crucial in addressing these challenges, particularly in the areas of system optimization, cost reduction, and the development of robust energy storage solutions.

The future of HRES is promising, with advancements in technology, such as smart grids, artificial intelligence, and predictive algorithms, offering new opportunities to enhance system performance and integration. As energy markets evolve and the costs of renewable energy components continue to decline, HRES will likely become an increasingly attractive option for both developed and developing countries. Their ability to provide reliable, sustainable, and cost-effective energy solutions positions them at the forefront of the global transition to a low-carbon economy.

In conclusion, hybrid renewable energy systems are poised to play a pivotal role in the future of energy generation, offering a pathway to sustainable development and energy resilience. By combining the strengths of solar and wind energy, along with efficient storage and management solutions, HRES provide a comprehensive approach to meeting the world's energy needs while addressing the urgent environmental challenges posed by climate change. The continued advancement and adoption of these systems will be instrumental in shaping a cleaner, greener, and more sustainable energy future for generations to come.

Chapter 2

Introduction to Artificial Intelligence in Renewable Energy Systems

2.1 Introduction

Artificial Intelligence (AI) is a field of computer science that ncludes developing systems capable of performing tasks that typically need human intelligence, such as learning, decision-making, and problem-solving. Over the past few decades, AI has made important strides, finding applications across various industries [79]. One area where AI has become particularly impactful is the energy sector, specifically in renewable energy systems. Integrating AI into energy systems offers favorable solutions for improving efficiency,optimisation, and sustainability. By enabling intelligent control, optimization, and predictive capabilities, AI helps manage some of the key challenges associated with renewable energy sources such as wind and solar power, which are naturally variable and difficult to manage with traditional control methods. The application of AI in renewable energy systems is especially crucial due to the growing global shift toward cleaner energy sources [109]. Solar and wind energy have become integral domains of the current energy mix, but their intermittency poses challenges to grid stability and efficient energy generation. AI methods help tackle these challenges by enabling real-time optimization and adaptive control of energy systems. For example, AI-driven algorithms can optimize maximum power point tracking (MPPT) in solar panels, providing that they are used at their highest efficiency even under unstable environmental conditions. Similarly, in wind energy systems, AI models can predict wind patterns, improve turbine control, and optimize energy production, all while reducing mechanical wear and tear on equipment. These advanced control and optimization capabilities lead to higher energy yields, reduced operative costs, and more reliable renewable energy systems [55]. AI obtains multiple advantages over renewable energy systems. One of the key advantages is its ability to improve control and automation. Traditional control techniques struggle with the complexity and nonlinearity of renewable energy systems, whereas AI-based controllers can manage these challenges with greater accuracy and adaptability. AI also improves energy system performance by optimizing energy results, permitting systems to continuously adapt to changes in environmental conditions and needs. Also, AI enables predictive maintenance, which can detect potential issues in energy systems before they lead to costly downtime. This predictive capability increases system reliability and decreases maintenance costs [70]. Another significant benefit of AI is its ability to adapt to new data, indicating that as envi-

ronmental conditions or energy request designs change, AI systems can develop and support optimal performance. Several AI techniques are especially well-suited to renewable energy applications, each offering special advantages. Fuzzy logic, for instance, is practical for handling uncertainty and imprecision in systems, making it useful for modelling the vagueness inherent in renewable energy resources like solar irradiance and wind speeds. Artificial neural networks (ANNs) are powerful mechanisms for learning complex patterns from data and have been widely used in energy prediction, system control, and optimization tasks. Their capacity to model nonlinear relationships and adjust to new data makes them ideal for dynamic energy systems. Another AI technique, the M5-Pruned decision tree, is a type of regression tree that is used for decision-making in continuous data environments. It is particularly beneficial in energy management and control because of its simplicity and ability to provide interpretable models that balance accuracy with computational efficiency [54]. This chapter will examine these three AI techniques fuzzy logic, artificial neural networks, and the M5-Pruned decision tree in detail. Each section will describe the fundamental principles behind these techniques, their applications in renewable energy systems, and the specific benefits they offer. The chapter will conclude with a comparative analysis of these techniques, highlighting their strengths and limits. Besides, hybrid systems, which incorporate the strengths of extra AI methods, will be discussed as potential solutions for further enhancing energy system performance. Through this exploration, the chapter aims to supply a comprehensive understanding of how AI can develop control and optimization in renewable energy systems, contributing to a more sustainable and efficient energy future.

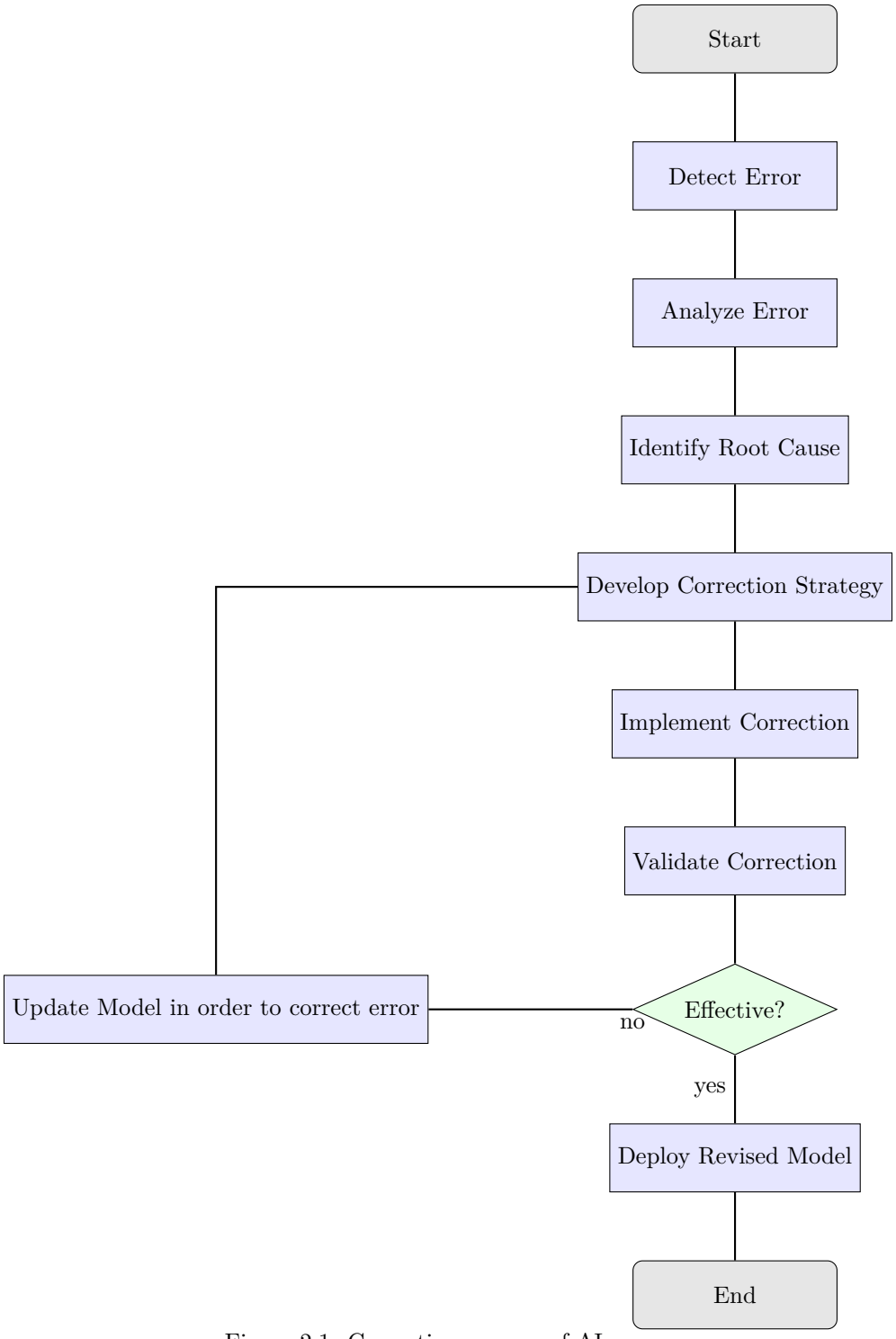


Figure 2.1: Correction process of AI errors

2.2 Fuzzy Logic

Fuzzy logic is a computational process that takes reasoning in systems indicated by uncertainty and imprecision. Unlike traditional binary logic, where variables can only take values of 0 or 1, fuzzy logic permits for a range of truth values between 0 and 1, illustrating partial truths [127]. This makes fuzzy logic particularly useful in real-world applications, where systems are often too complex or uncertain to be defined by rigid binary classifications. Instead of operating hard thresholds, fuzzy logic presents the concept of “degrees of truth,” enabling it to model the vagueness inherent in many natural procedures, including those found in renewable energy systems. The concept of fuzzy logic was first presented by Lotfi Zadeh in 1965 as a way to mathematically describe uncertain or vague data. Fuzzy logic creates upon the idea of fuzzy sets, where an element can partially belong to a set, with a membership function defining the degree of belonging. For instance, in traditional logic, a temperature might be classified as either "hot" or "cold," but in fuzzy logic, a temperature could be "somewhat hot" or "very hot" founded on its degree of membership in the "hot" set. This flexibility permits fuzzy logic to regulate continuous and nonlinear systems more effectively than rigid binary systems [21]. In renewable energy systems, fuzzy logic is often employed for control and optimization tasks, where precise modelling of input variables is hard due to the variability of natural resources [129]. For example, in a solar energy system, sunlight intensity and temperature can fluctuate throughout the day, affecting the system’s performance. A fuzzy logic-based controller can adapt to these changes by interpreting input values as fuzzy sets and using a set of fuzzy rules to make decisions. This adaptive control capability is particularly valuable for systems like solar panels or wind turbines, where requirements change constantly, and traditional control systems may struggle to support optimal performance. Fuzzy logic is used through a process named fuzzy inference, which includes mapping inputs to outputs established on predefined fuzzy rules. Two of the most standard fuzzy inference methods are the Mamdani and Sugeno inference systems. In a Mamdani inference system, input variables are mapped to fuzzy sets, and a set of "if-then" rules is applied to select the output, which is then defuzzified to construct a crisp value. Sugeno inference, on the other hand, generates mathematical functions as outputs rather than fuzzy sets, offering more uncomplicated computational requirements. Both inference systems are widely employed in renewable energy systems, with Mamdani being preferred for systems needing human-like reasoning, and Sugeno being used in real-time control systems due to its computational efficiency.

In the context of renewable energy, fuzzy logic has been applied to a wide scope of systems, including solar energy, wind energy, and hybrid power systems. For example, in (MPPT)

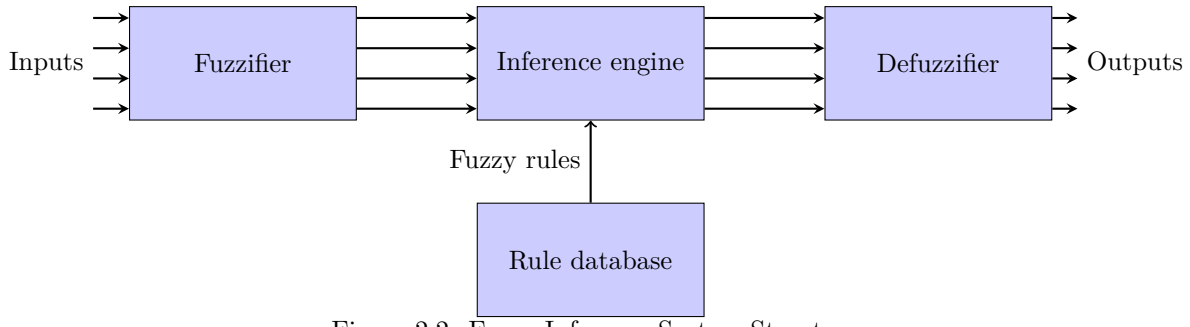


Figure 2.2: Fuzzy Inference System Structure

algorithms for photovoltaic (PV) systems, fuzzy logic is used to optimize the extraction of power from solar panels, even under changing sunlight conditions [57]. In wind power, fuzzy logic controllers can be employed to address turbine settings dynamically based on wind speed changes, guaranteeing that the system works efficiently via a wide scope of conditions. Fuzzy logic has also been employed in hybrid renewable power systems, allowing to management of the interaction between various energy sources and storage systems to maintain balance and stability in grid-connected systems.

2.2.1 Fuzzy Sets and Membership Functions

Fuzzy sets are the foundational concept in fuzzy logic, qualifying for the expression of vague or imprecise information. Unlike classical sets, where an element either belongs to a set or does not (with a membership value of either 0 or 1), fuzzy sets allow for degrees of membership. This represents an element that can partially belong to a fuzzy set, with its membership defined by a value between 0 and 1. This flexibility constructs fuzzy sets as an ideal mechanism for modelling real-world systems where the borders between categories, such as temperature, speed, or energy generation levels in renewable power systems, are not sharply defined. In a fuzzy set, each component is associated with a membership function that defines the degree to which the element belongs to the set. A membership function is a curve that sets to each possible input a membership value (also called a grade of membership) varying from 0 to 1. For instance, consider a fuzzy set denoting"warm temperature." A specific temperature, such as 25°C, may have a membership value of 0.8 in the "warm" fuzzy set, meaning that it is supposed to be 80% warm. At the same time, it might have a membership value of 0.2 in the "cold" fuzzy set, displaying some partial overlap between the two types. Membership functions can assume different forms, relying on the nature of the fuzzy set and the issue being modelled. Some common kinds of membership functions include:

- Triangular Membership Function: This is one of the most uncomplicated forms of membership functions. It is described by a triangular shape, represented by three parameters: the lower bound, the peak, and the upper bound. The membership value rises linearly from the lower bound to the peak and reduces linearly from the peak to the upper bound. Example: For a fuzzy set representing "medium speed" in a wind turbine control system, a triangular membership function might assign full membership (value = 1) to a wind speed of 10 m/s, while speeds below 5 m/s or above 15 m/s might have a membership value of 0.

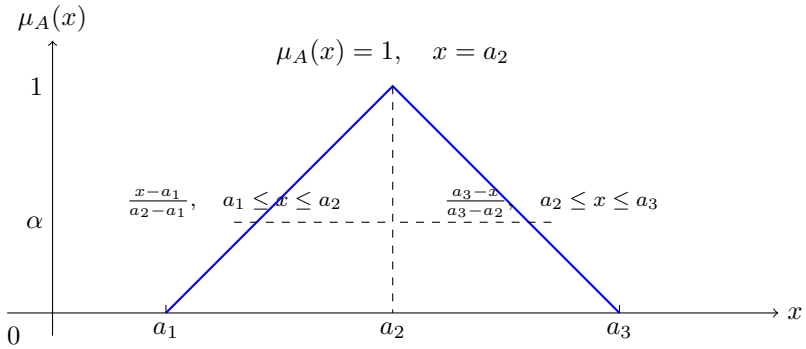


Figure 2.3: Triangular Membership Function Representation

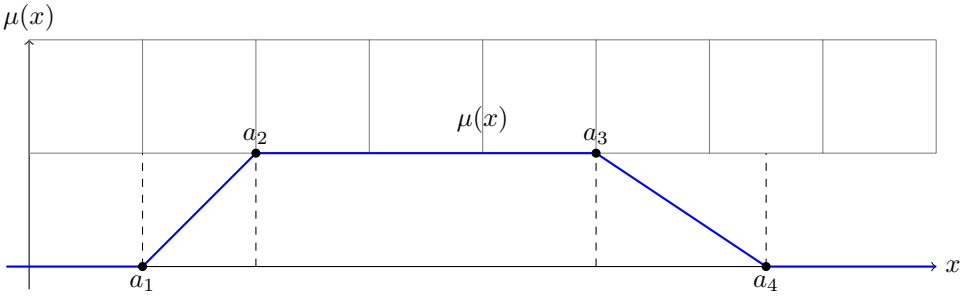


Figure 2.4: trapezoidal membership function

The triangular membership function is mathematically defined as:

$$\mu_A(x) = \begin{cases} 0, & x \leq a_1 \text{ or } x \geq a_3, \\ \frac{x-a_1}{a_2-a_1}, & a_1 \leq x \leq a_2, \\ \frac{a_3-x}{a_3-a_2}, & a_2 \leq x \leq a_3. \end{cases}$$

where:

- a_1 is the left base of the triangle.
- a_2 is the peak where $\mu_A(x) = 1$.
- a_3 is the right base of the triangle.

- Trapezoidal Membership Function: This function is an extension of the triangular membership function, where the top of the trapezoid represents a range of values that have full membership (value = 1). It is characterized by four parameters: two defining the base of the trapezoid and two defining the top. Example: A trapezoidal membership function might be used to represent "adequate sunlight" in a solar energy system, with a flat top indicating that any sunlight intensity between 500 W/m^2 and 800 W/m^2 is considered fully adequate, while intensities outside this range gradually taper off.

  The trapezoidal membership function is defined as:

$$\mu(x) = \begin{cases} 0, & x \leq a_1 \\ \frac{x-a_1}{a_2-a_1}, & a_1 \leq x \leq a_2 \\ 1, & a_2 \leq x \leq a_3 \\ \frac{a_4-x}{a_4-a_3}, & a_3 \leq x \leq a_4 \\ 0, & x \geq a_4 \end{cases}$$

  where $a_1 \leq x \leq a_2$ and $a_3 \leq x \leq a_4$.

- Gaussian Membership Function: This is a smooth, bell-shaped function defined by two parameters: the centre (mean) and the spread (standard deviation). It is commonly used in fuzzy systems where a smooth transition between categories is needed [68]. Example: In a temperature control system, a Gaussian membership function could represent "moderate temperature," with the highest membership value at 25°C and membership values decreasing smoothly as the temperature moves further from this centre point.

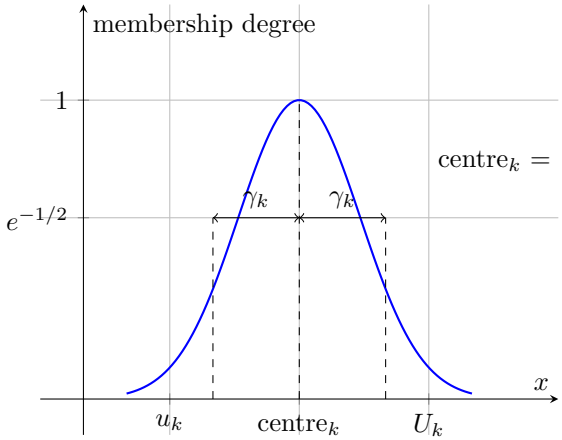


Figure 2.5: Gaussian Membership Function

The Gaussian membership function is given by:

$$\mu(x) = e^{-\frac{(x-\text{centre}_k)^2}{2\gamma_k^2}} \tag{2.1}$$

where:

- $\mu(x)$ is the membership degree (ranging from 0 to 1).
- centre$_k$ is the midpoint, given by:

$$\text{centre}_k = \frac{u_k + U_k}{2} \tag{2.2}$$

- γ_k is the spread parameter determining the width.
- u_k and U_k are the lower and upper bounds.
- The function peaks at $x = \text{centre}_k$ with $\mu(x) = 1$.
- At $x = \text{centre}_k \pm \gamma_k$, the membership value is $e^{-1/2} \approx 0.6065$.

- Sigmoidal Membership Function: This function has an S-shaped curve and is useful for modeling situations where the transition between categories is gradual but nonlinear. It is particularly useful when there is a need to model asymmetrical behaviors. Example: A sigmoidal membership function might be applied to represent "high wind speed," where very low speeds have almost no membership, but as the speed increases past a certain point, the membership value rises sharply.

  The sigmoid function is given by:

$$sig(t) = \frac{1}{1 + e^{-t}} \tag{2.3}$$

These membership functions form the backbone of fuzzy logic systems, translating real-world measurements (such as wind speed, solar irradiance, or temperature) into fuzzy values that can be processed by a fuzzy controller. The choice of the membership function depends on the specific characteristics of the system being modelled and the desired behaviour of the control system. In renewable energy systems, fuzzy sets and their corresponding membership functions are essential for handling the uncertainty and

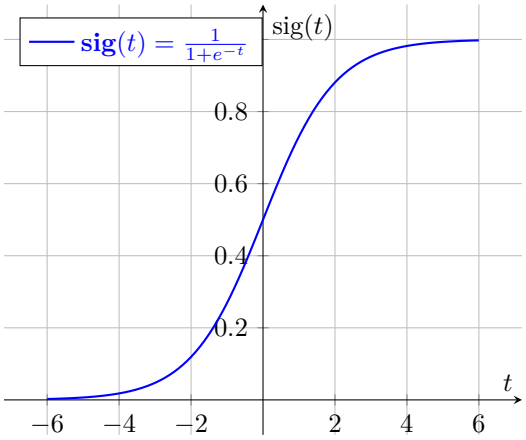


Figure 2.6: Sigmoidal Membership Function

variability inherent in natural resources like wind and sunlight. For instance, in Maximum Power Point Tracking (MPPT) algorithms for solar photovoltaic systems, fuzzy sets can be used to represent input variables such as sunlight intensity and temperature. These fuzzy inputs are then processed using a set of fuzzy rules to determine the optimal operating point for the system, enabling it to adapt to changing environmental conditions and maximize power output. In conclusion, fuzzy sets and membership functions play a crucial role in the implementation of fuzzy logic controllers. By allowing for partial membership and smooth transitions between categories, they provide the flexibility needed to model the continuous, nonlinear, and uncertain behavior of renewable energy systems. This capability is particularly important in applications like wind turbine control, solar energy optimization, and hybrid energy management, where precise control is often difficult to achieve using traditional binary logic systems.

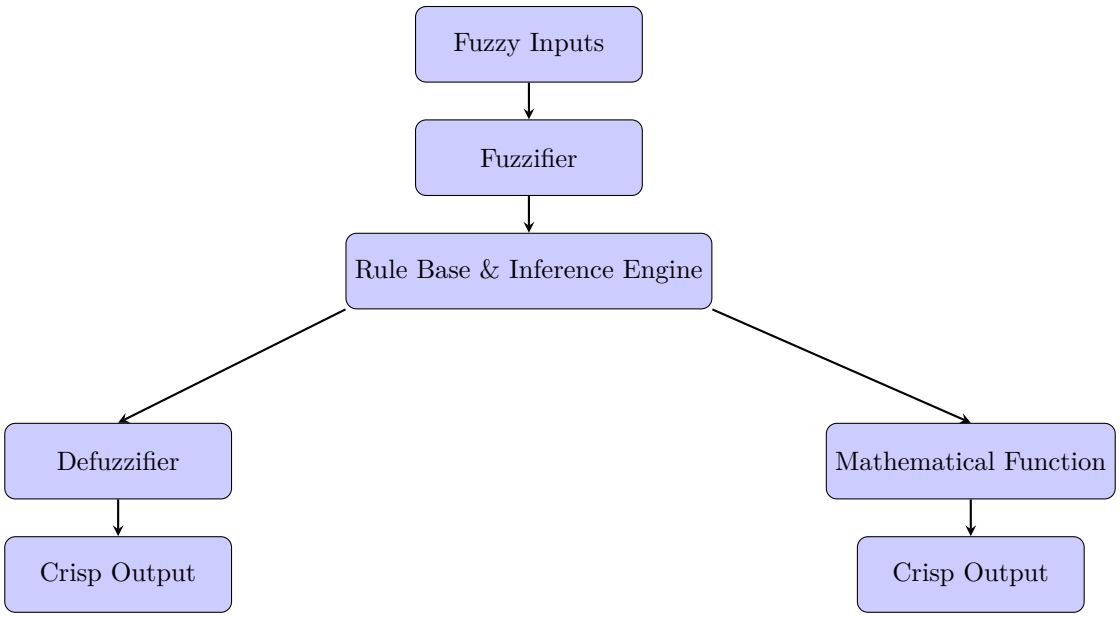
2.2.2 Fuzzy Inference Systems

Fuzzy Inference Systems (FIS) are frameworks that translate inputs into outputs based on the concepts of fuzzy logic. They are utilized for decision-making, control systems, and modeling complicated structures characterized by uncertainty and imprecision [128].

2.2.2.1 Key Components of a Fuzzy Inference System

1. **Fuzzification**: Converts crisp input values into fuzzy sets via predefined membership functions. These functions translate the input variables to a degree of membership, typically between 0 and 1.
2. **Rule Base**: A set of "if-then" rules, which are usually designed from expert knowledge. Each rule describes a fuzzy relationship between input and output variables. The rules typically form as:

   IF (condition on input variables) THEN (output).
3. **Inference Engine**: Processes the fuzzy input and applies the fuzzy rules to infer the output. It estimates the degree to which each rule is used and integrates the results to create fuzzy outputs.



(A) Mamdani FIS (B) Sugeno FIS

Figure 2.7: Comparison of Mamdani and Sugeno Fuzzy Inference Systems

4. **Aggregation**: The process of integrating the fuzzy outputs of all rules into a single fuzzy set. This typically uses fuzzy operators such as max (for OR) and min (for AND).
5. **Defuzzification**: Converts the aggregated fuzzy output back into a crisp value, representing the system's final output. The defuzzification methods include:
   - Centroid method: Finds the center of the area under the curve.
   - Mean of maximum (MOM): Uses the average of the maximum values.
   - Bisector method: Divides the area under the curve into two equal parts.

2.2.3 Types of Fuzzy Inference Systems

2.2.3.1 Mamdani FIS

Mamdani FIS is the most common type of fuzzy inference system. It operates using min-max operations for fuzzy rules and employs the centroid technique for defuzzification. This type is well-suited for designs where expert knowledge is available.

2.2.3.2 Sugeno FIS

The output of a Sugeno FIS is either a constant or a linear function of the input variables. Control systems that require highly accurate output values frequently employ this computationally efficient method.

2.2.4 Tsukamoto FIS

This system is similar to Sugeno but outputs fuzzy sets with monotonic membership functions. The final output is derived by averaging the output per rule.

2.2.5 Applications of Fuzzy Inference Systems

2.2.5.1 Control Systems

FIS is used in control systems such as air conditioning, braking, and robotics, where human-like reasoning can enhance complex control mechanisms.

Decision Making Fuzzy inference is applied in medical diagnosis, financial systems, and risk management to handle imprecision in decision-making processes.

2.2.5.2 Pattern Recognition

FIS is useful in classifying data patterns, speech recognition, and image processing, particularly in scenarios where sharp boundaries between categories do not exist.

2.2.5.3 Role of Fuzzy Logic in Energy Systems

Fuzzy logic has gained significant importance in controlling and optimizing energy systems. Its ability to handle uncertainties and imprecise inputs makes it particularly useful for renewable energy sources such as solar and wind, which are highly variable and nonlinear. Traditional control methods often struggle to manage these fluctuations, whereas fuzzy logic, with its rule-based system and human-like reasoning, provides a robust solution for dynamic environments.

2.2.5.4 Applications in Solar Energy Systems

The unpredictable nature of solar irradiance, influenced by factors such as cloud cover and temperature variations, presents challenges in controlling solar energy systems. Fuzzy logic offers an intelligent solution for handling these uncertainties, ensuring higher efficiency in energy harvesting and conversion.

2.2.5.5 Maximum Power Point Tracking (MPPT)

Fuzzy logic controllers are commonly used for MPPT in photovoltaic (PV) systems. By applying fuzzy rules, these controllers track the maximum power point of a PV panel, even under rapidly changing irradiance and temperature conditions. Unlike conventional techniques, fuzzy logic-based MPPT adjusts output voltage and current efficiently without requiring precise mathematical models of the PV system.

Advantages:

- Faster convergence to the maximum power point.
- Robustness against noise and instabilities in solar irradiance.
- Better handling of partial shading conditions.

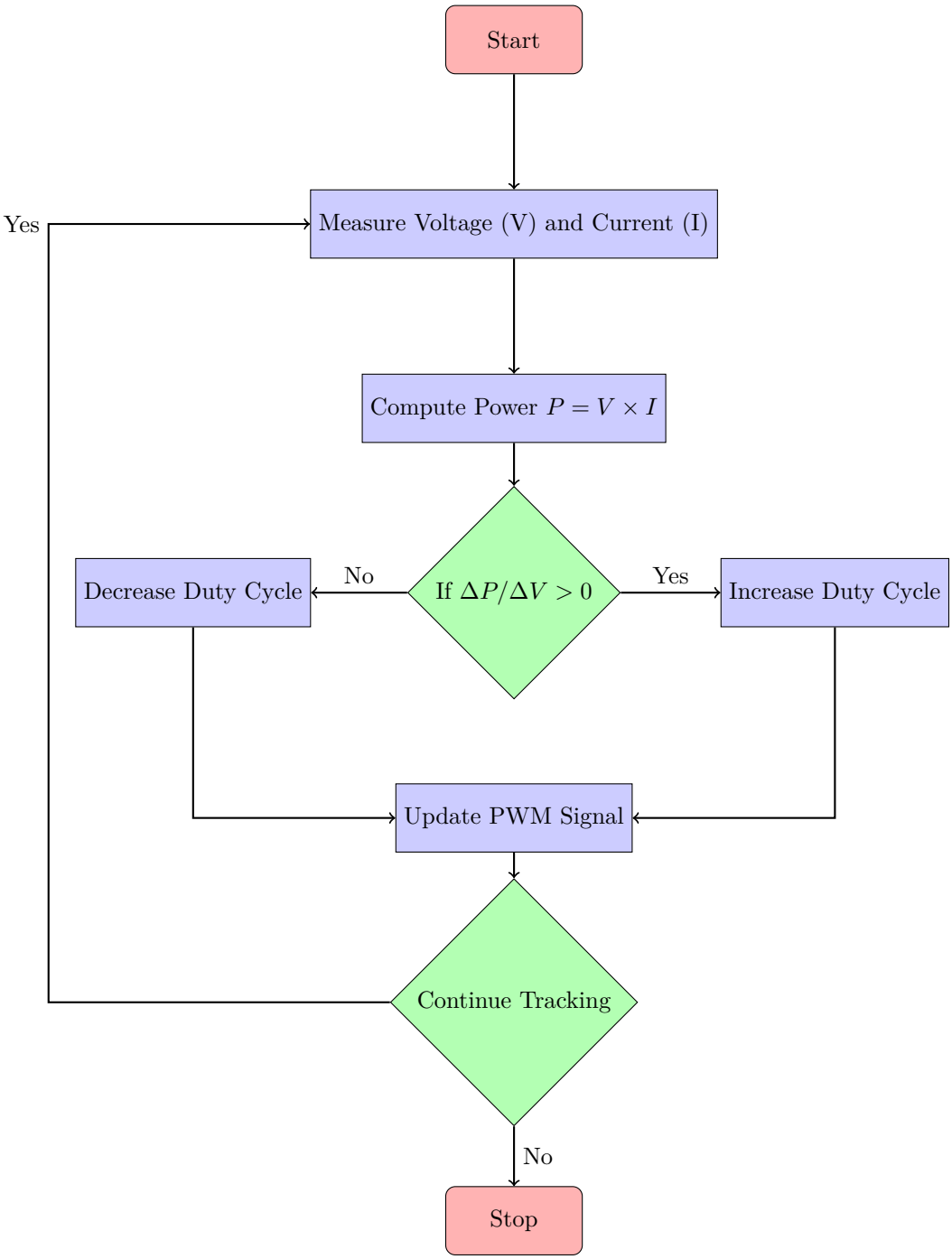


Figure 2.8: MPPT strategy

Energy Storage Management In hybrid solar energy systems with battery storage, fuzzy logic optimizes energy storage and discharge by evaluating factors such as battery charge levels, irradiance, and load demand. This approach improves energy distribution between storage and the grid.

Solar Water Heaters Fuzzy logic is applied to enhance the efficiency of solar water heating systems. It adjusts parameters such as water flow speed and heater temperature based on solar energy availability and user demand [9].

Grid Integration and Power Quality In grid-connected PV systems, fuzzy logic regulates voltage and current to maintain power quality. It ensures smooth synchronization of the PV system with the grid and facilitates stable power delivery, even under fluctuating solar input.

2.2.6 Wind Energy Control with Fuzzy Logic

Wind energy systems also benefit significantly from the flexibility of fuzzy logic control, particularly due to the variability in wind speed and direction. Fuzzy logic has been utilized in several components of wind energy conversion systems (WECS), enhancing their efficiency and reliability under fluctuating environmental conditions. Key applications include:

2.2.6.1 Pitch Angle Control

In wind turbines, the pitch angle of the blades must be adjusted according to wind speed to maximize power output and protect the turbine from damage at high speeds. Fuzzy logic controllers dynamically regulate the pitch angle by considering the wind speed and rotor speed, ensuring optimal power extraction and turbine protection. Conventional control techniques may be less responsive or require precise mathematical models, whereas fuzzy logic controllers can adapt to the system's inherent uncertainties.

2.2.6.2 Maximum Power Point Tracking (MPPT)

Similar to solar systems, fuzzy logic is employed in wind energy systems to track the maximum power point. Wind speeds can change rapidly, and the nonlinear nature of power generation from wind turbines complicates control. A fuzzy logic MPPT controller continuously adjusts the rotor speed and generator torque to match the optimal operating point, even under rapidly varying wind conditions.

2.2.6.3 Generator Control

In variable-speed wind turbines, fuzzy logic assists in controlling the turbine's generator, ensuring efficient operation across different wind speeds. The controller manages parameters such as electromagnetic torque to align with wind speed while preventing mechanical stress and energy losses.

2.2.7 Grid Stability and Power Quality

For grid-connected wind energy systems, maintaining stability and power quality is crucial. Fuzzy logic control helps regulate reactive power, harmonics, and voltage fluctuations in wind energy systems, ensuring smooth integration of the wind turbine with the electrical grid, even under unstable wind conditions.

2.2.8 Yaw Control

Yaw control systems orient wind turbines to face the wind direction for maximum efficiency. Fuzzy logic-based yaw controllers compensate for imprecisions in wind direction measurements, ensuring smooth adjustments to optimize energy capture while minimizing wear on the turbine structure. This function is widely used in fuzzy logic systems for defining fuzzy sets.

2.3 Artificial Neural Nerwork control

Artificial Neural Networks (ANNs) are computational models inspired by the structure and functioning of the human brain. In control systems, ANNs are used to model, learn, and forecast the system behavior of complex dynamic systems. ANNs have become especially invaluable in cases where traditional control methods, such as PID or model-based ones, struggle to cope with nonlinearity, uncertainty, or time-varying system parameters.

Learning from data is another important benefit of ANN control. As opposed to requiring an accurate mathematical model of the system, an ANN can be trained using past input-output data to approximate the system's behavior. This makes ANN-based controllers very flexible and usable for systems that are difficult or impossible to model algebraically.

ANNs are also adaptable. Once trained, they can adapt to system dynamic change and are thus ideal for real-time and adaptive control applications. This is particularly advantageous in those applications where system behavior evolves with time, for instance, renewable energy systems, electric vehicle systems, and industrial automation.

Several neural network structures are used in control systems. The most basic and typically used for static function approximation is the feedforward neural networks (FANNs). Recurrent neural networks (RNNs) have internal feedback loops to handle time-varying and dynamic systems. Radial basis function (RBF) networks offer training speed and optimal localized learning for use in adaptive control applications.

Different methods of control can be achieved using ANNs. Under direct ANN control, the network generates control signals directly from system inputs. Under indirect control, ANNs are used to estimate parameters or dynamics of a model that are fed as inputs to a conventional controller. Other advanced techniques include ANN-based MPC as well as neuro-fuzzy control, which combines ANN learning and fuzzy logic reasoning.

ANN control is widely applied in various applications in areas such as renewable energy systems (e.g., maximum power point tracking of solar panels), robotics, smart grids, electric drives, and power electronics (e.g., DTC or DPC of converters). Its ability to

handle nonlinearity, uncertainty, and multiple-input–multiple-output (MIMO) systems makes it a successful tool for use in intelligent controls in the contemporary age.

Although it has its benefits, ANN control also has some challenges. Neural network training necessitates high-quality data in large quantities, and the computational load may be high, particularly in cases of deep or very complex architectures. Moreover, ANNs tend to be regarded as black-box models, and the internal decision-making mechanisms are not transparent, which can be problematic in safety-critical environments.

In summary, ANN-based control offers a promising alternative to traditional control methods for uncertain, nonlinear, or high-data-rate systems. Its learning and adaptability open up new opportunities in intelligent automation and optimal energy utilization, but care is taken during design, training, and testing to ensure robust and stable operation.

2.3.1 Components of Artificial Neural Network Control

Artificial neural network (ANN) control systems consist of several essential components that work together to learn and execute control actions effectively. The key components are as follows:

- **Input Layer:** Receives process variables or measurements such as voltage, current, or temperature. These inputs influence the control output and are often normalized.
- **Hidden Layer(s):** Composed of neurons that apply weighted sums and activation functions to inputs. They perform nonlinear transformations and extract features necessary for control.
- **Weights and Biases:** Trainable parameters of the network. They are adjusted during training to minimize the error between predicted and actual outputs.
- **Activation Function:** Introduces non-linearity into the model, enabling it to approximate complex functions. Common functions include ReLU, sigmoid, and tanh.
- **Output Layer:** Produces the final control signal, such as a reference value or switching signal for power converters.
- **Training Algorithm:** Optimizes weights and biases using algorithms like backpropagation with gradient descent or Levenberg–Marquardt.
- **Error Function (Loss Function):** Measures the difference between desired and predicted outputs. Common examples include Mean Squared Error (MSE).
- **Learning Rate and Epochs:** Define how quickly the network learns and how many times the data is passed through the model during training.
- **Validation Mechanism:** Ensures the ANN generalizes well by evaluating performance on unseen data and preventing overfitting.

2.3.2 Role of Artificial Neural Networks (ANNs) in Development

Artificial Neural Networks (ANNs) have emerged as a powerful tool for advancing the development of intelligent systems across numerous fields. Their ability to learn from data and approximate complex nonlinear relationships makes them ideal for addressing

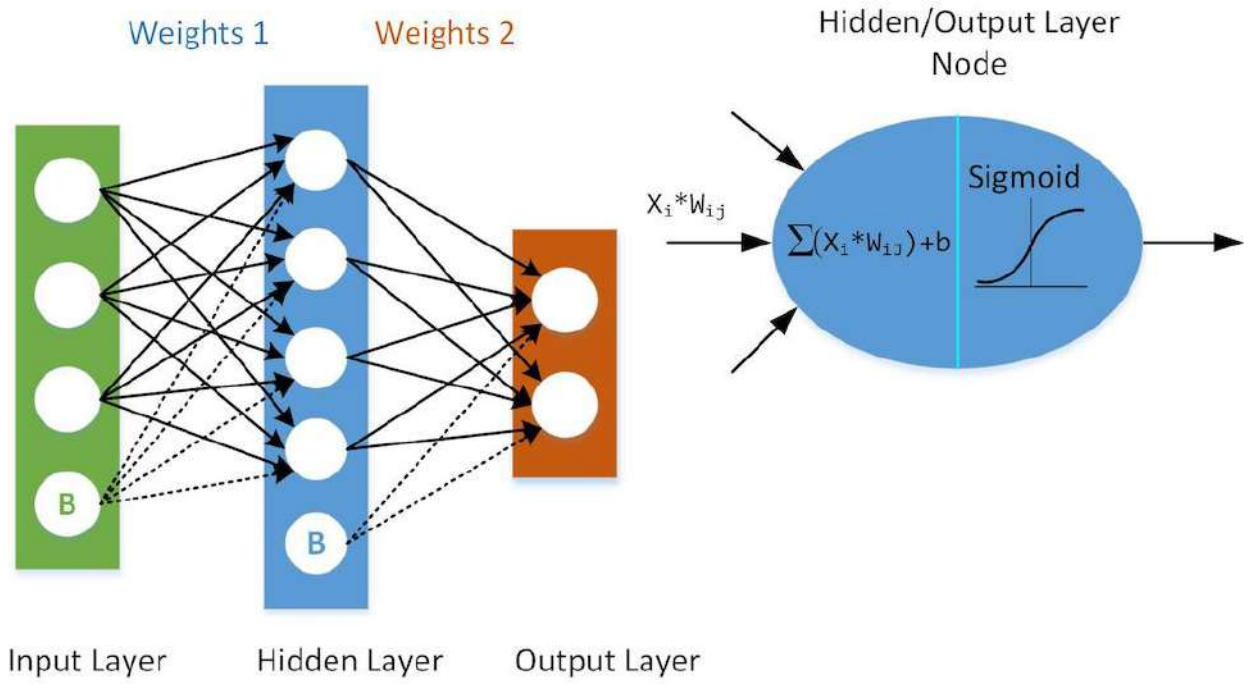


Figure 2.9: Components of Artificial Neural Network

Table 2.1: Comparison between Artificial Neural Network (ANN) and Neural Network (NN) [59]

Aspect	**Artificial Neural Network (ANN)**	**Neural Network (NN)**
Terminology	Formal and complete term used to describe computational models inspired by the brain.	Abbreviated or general term, often used interchangeably with ANN.
Definition	A machine learning model with layers of neurons designed to approximate complex functions.	Broad term that can include all ANN types and even biologically inspired networks.
Common Usage	Frequently used in control, signal processing, and classical machine learning literature.	Often used in modern AI, deep learning, and casual discussions.
Scope	Typically refers to shallow feedforward networks (1–2 hidden layers).	May refer to any neural network, including deep, convolutional, and recurrent networks.
Training	Uses backpropagation, gradient descent, etc., to minimize error.	Same training methods apply. NN is a more generic term.
Applications	Used in control systems, energy systems, fault detection, etc.	Includes all ANN applications and more complex AI models.
Deep Learning Context	Refers more to simpler, shallow networks.	Includes all deep learning architectures (DNNs, CNNs, RNNs, etc.).
Interpretation	A structured type of NN focused on artificial intelligence.	Can also refer to biological neural networks in neuroscience.

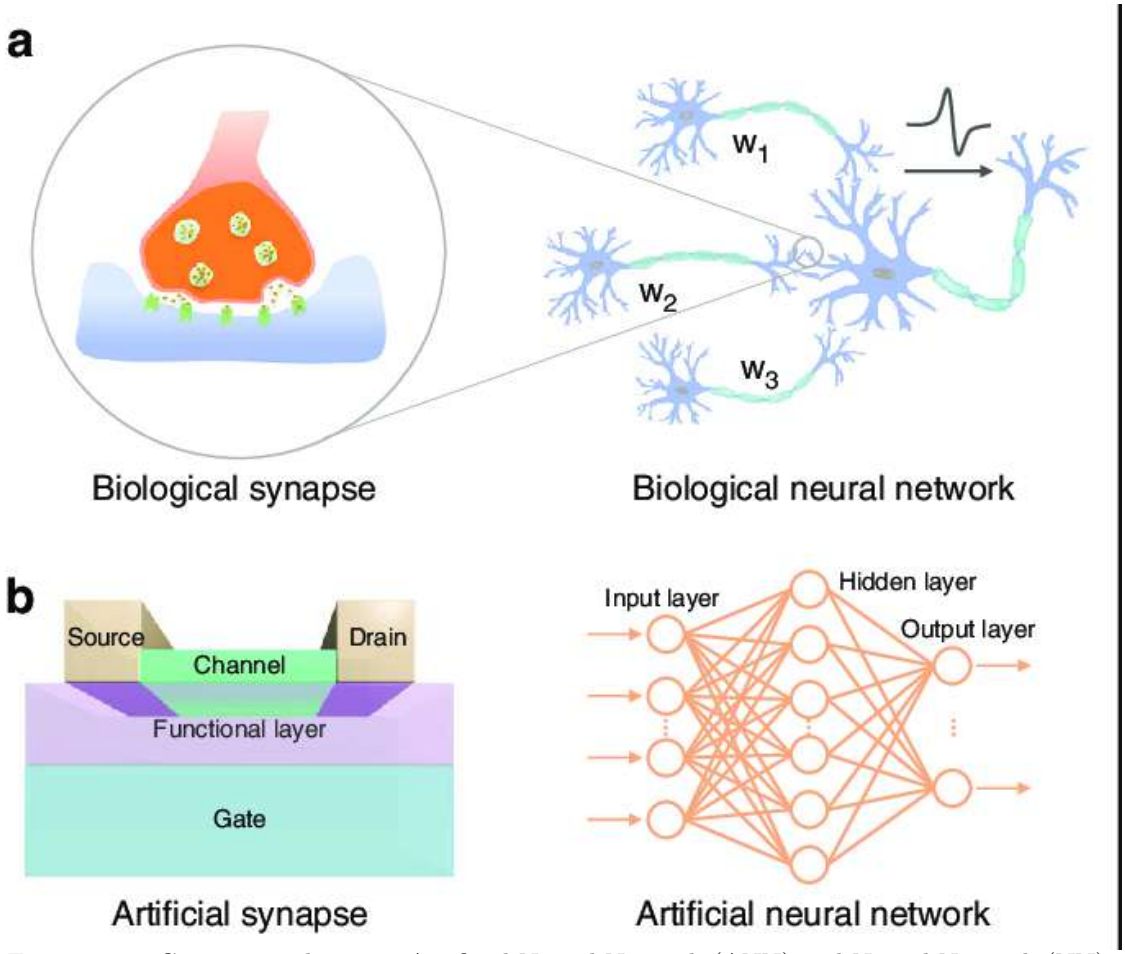


Figure 2.10: Comparison between Artificial Neural Network (ANN) and Neural Network (NN)

problems where traditional analytical models are insufficient or infeasible. ANNs play a transformative role in sectors ranging from renewable energy and automation to healthcare and smart infrastructure [73].

In engineering and control systems, ANNs contribute significantly to the optimization and automation of industrial processes. They allow for the design of adaptive controllers that can respond to varying operational conditions without requiring an accurate mathematical model of the system. This capability enhances the efficiency, reliability, and responsiveness of modern energy systems, including microgrids, electric drives, and hybrid renewable energy systems.

In the energy sector, especially in the integration of solar and wind power, ANNs are widely used for tasks such as Maximum Power Point Tracking (MPPT), energy demand forecasting, and power quality control. By learning from environmental and operational data, ANNs can adapt to changes in irradiance, temperature, or wind speed, ensuring optimal power extraction and improving overall system stability.

The role of ANNs extends into predictive maintenance and fault detection, where they help reduce downtime and maintenance costs. By analyzing sensor data in real-time, neural networks can detect anomalies and predict failures before they occur. This predictive capability supports the transition to smart factories and Industry 4.0 paradigms.

Moreover, ANNs support sustainable development by enabling smart control systems that reduce energy waste and emissions. Their application in energy management systems (EMS) allows for more accurate load forecasting, real-time optimization of energy flows, and the integration of distributed energy resources. This contributes directly to the development of smarter, greener cities and infrastructures.

In summary, artificial neural networks are key enablers in the development of intelligent, autonomous, and efficient systems. Their data-driven nature, adaptability, and robustness position them at the forefront of innovations that drive progress in technology, sustainability, and digital transformation.

2.3.3 Recently Developed Algorithms in Artificial Neural Networks (ANNs)

Recent advances in Artificial Neural Networks (ANNs) have led to the development of numerous efficient and robust algorithms. These algorithms improve the learning speed, adaptability, and generalization ability of ANNs in complex applications such as control systems, renewable energy optimization, and automation. The most significant recent algorithms include:

1. **Backpropagation with Adaptive Learning Rates (Adam, RMSProp, Nadam):** Modern optimizers like Adam integrate momentum and adaptive step sizes to accelerate and stabilize convergence in ANN training, especially in noisy or non-stationary environments.
2. **Deep Neural Networks (DNNs):** Multi-layer networks that extract high-level features, DNNs have extended ANN capabilities for modeling highly nonlinear and complex systems in real-world applications.
3. **Residual Learning (ResNet-style Networks):** Residual connections help overcome vanishing gradient problems, enabling the training of very deep networks with improved accuracy and efficiency.

4. **Spiking Neural Networks (SNNs):** These biologically inspired models use discrete spike signals for computation, offering high efficiency and low energy consumption, particularly in embedded and IoT-based control systems.
5. **Extreme Learning Machines (ELM):** ELMs train single-layer feedforward networks extremely fast by randomly initializing input weights and only training the output weights analytically.
6. **Convolutional Neural Networks (CNNs) for Time-Series:** 1D CNNs are used to extract temporal features from time-series data in power quality analysis, load forecasting, and signal classification in energy systems.
7. **Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM):** These networks are designed for sequential data modeling, making them suitable for dynamic system prediction, wind/solar forecasting, and real-time control.
8. **Neuro-Fuzzy and Hybrid Models (e.g., ANFIS):** ANNs combined with fuzzy logic systems improve both learning efficiency and interpretability, widely applied in MPPT, power flow regulation, and hybrid energy management.
9. **Reinforcement Learning (RL)-Based ANN Controllers:** These systems learn optimal control policies through environment interaction, offering promising solutions in autonomous energy trading, microgrid operation, and smart control.
10. **Transfer Learning in Control Applications:** This approach enables pre-trained ANN models to be reused in new, similar tasks with minimal retraining, reducing the data requirement and accelerating deployment in energy applications.

2.3.4 M5P (M5-Pruned Model Tree Algorithm)

The M5P algorithm, or the M5-Pruned Model Tree, is a solid and understandable machine learning technique that unites decision tree induction with linear regression. First developed by Quinlan and later further developed in WEKA's incarnation as M5P, this algorithm is highly effective at handling regression problems where discrete splits and linear relationships both exist in various regions of the input space [65].

M5P assumes that most complex, nonlinear problems can be broken down into easy, piecewise-linear regions. It builds a decision tree structure for dividing the input space into regions and then induces a multivariate linear regression model in each leaf node. This hybrid strategy allows the algorithm to work effectively in applications such as intelligent control systems, renewable energy forecasting, real-time power control, and fault diagnosis, where both interpretability and predictive accuracy are essential.

2.3.4.1 Operational work of M5P Algorithm

The construction of an M5P model typically follows four major phases that combine decision tree induction with local linear regression modeling. These steps are enumerated as follows:

1. **Tree Construction Phase:**
   The algorithm recursively partitions the input space by selecting split attributes that maximize the expected reduction in the standard deviation of the target variable.

Table 2.2: Advantages and Disadvantages of Recently Developed ANN Algorithms [73]

Algorithm	Advantages	Disadvantages
Backpropagation with Adaptive Learning Rates (Adam, RMSProp, Nadam)	Fast convergence, robust to noisy data, minimal tuning needed	May converge to suboptimal minima, performance sensitive to learning rate initialization
Deep Neural Networks (DNNs)	Capable of learning complex features, high accuracy for nonlinear systems	Requires large datasets and computational power, prone to overfitting
Residual Networks (ResNet)	Enables very deep architectures, mitigates vanishing gradient problem	Increased model complexity, longer training time
Spiking Neural Networks (SNNs)	Energy-efficient, biologically plausible, good for embedded systems	Difficult to train, limited tools and frameworks
Extreme Learning Machines (ELM)	Extremely fast training, suitable for real-time applications	Random initialization may lead to inconsistency, limited adaptability
Convolutional Neural Networks (CNNs for Time-Series)	Effective at feature extraction from signals, good generalization	Not ideal for long temporal dependencies without modification
Recurrent Neural Networks (RNNs) and LSTM	Good for sequence learning and dynamic system modeling	Long training time, vanishing gradient issue in standard RNNs
Neuro-Fuzzy (e.g., ANFIS)	Interpretability and adaptability, combines logic and learning	Scalability issues with large input spaces, more tuning required
Reinforcement Learning (RL)-Based ANN	Learns directly from interaction, no explicit model required	Requires many episodes to train, may be unstable
Transfer Learning	Reduces training time, needs less data, effective with related tasks	Risk of negative transfer if source and target domains differ significantly

This is conceptually similar to minimizing prediction error. Each internal node in the tree represents a decision rule (e.g., $X > 3.2$) that separates the dataset into subsets with lower output variance [76].

2. **Model Building at the Leaves:**
   Unlike typical regression trees that assign constant values at the leaves, M5P fits a multivariate linear regression model at each leaf. These models are trained using the data points that reach the respective leaf node, enabling accurate predictions based on a linear combination of selected input features.

3. **Pruning and Simplification:**
   After the initial tree is constructed, M5P applies a pruning phase to eliminate overfitting. Subtrees that do not significantly reduce prediction error are replaced with their corresponding linear regression models. This helps simplify the model while maintaining high generalization capability.

4. **Smoothing (Optional):**
   To improve prediction continuity, particularly near the boundaries of leaf regions, M5P can apply a smoothing mechanism. This process blends the prediction from a leaf's linear model with the model of its parent node, reducing sharp discontinuities in the predicted output.

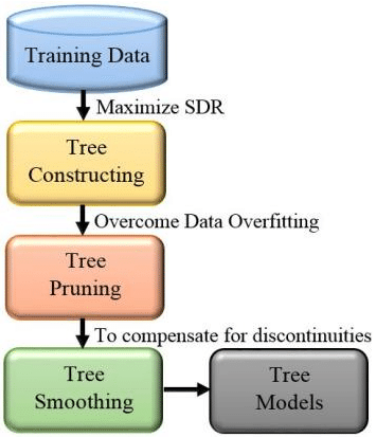


Figure 2.11: Operational work of M5P Algorithm

2.3.4.2 Applications of M5P in Control and Energy Systems

The M5P algorithm has been successfully applied across various engineering domains, especially in intelligent control and energy systems. Its ability to combine decision rules with regression modeling makes it particularly suitable for complex, data-driven applications [103].

1. **Renewable Energy Systems:**
   In photovoltaic and wind energy systems, M5P is employed to design intelligent Maximum Power Point Tracking (MPPT) controllers. These controllers adapt in real time to changing environmental conditions such as irradiance and temperature, ensuring optimal energy extraction [102].
2. **Hybrid Solar-Wind Systems:**
   M5P assists in modeling and forecasting power output from hybrid sources by analyzing multiple input variables like solar irradiance, wind speed, and system load. Its localized linear models enable accurate prediction in systems with varying energy dynamics.
3. **Smart Grid Applications:**
   The algorithm supports short-term and long-term energy demand forecasting in smart grids. By anticipating consumption patterns, it enables efficient load balancing, demand-side management, and optimization of energy distribution.
4. **Fault Detection and Diagnosis:**
   In industrial and power systems, M5P is used for fault classification and system health monitoring. It enables rule-based decision-making while leveraging regression estimates to identify anomalies and predict failure conditions with high precision.

2.3.4.3 Step-by-Step Workflow for Generating the M5P Model Using WEKA

To develop and evaluate the M5P model, the open-source data mining tool **WEKA** (Waikato Environment for Knowledge Analysis) was employed. The process of generating the M5P model using WEKA involves several key steps, outlined as follows:

Table 2.3: Advantages and Disadvantages of the M5P Algorithm [33]

Advantages	**Disadvantages**
Combines decision trees with linear regression, offering both interpretability and precision	May perform poorly in highly nonlinear systems without clear local linear regions
Provides transparent and explainable models suitable for engineering and control systems	Sensitive to noisy data and irrelevant features if not properly preprocessed
Efficient in terms of training time and computational resources, suitable for real-time applications	Tree structure may vary significantly with small changes in the training dataset (instability)
Supports pruning and smoothing, which improve generalization and prediction continuity	Less flexible than neural networks or ensemble methods for complex, high-dimensional tasks
Capable of modeling systems with piecewise-linear behavior, common in control and energy systems	Limited tool availability and less community support compared to mainstream algorithms

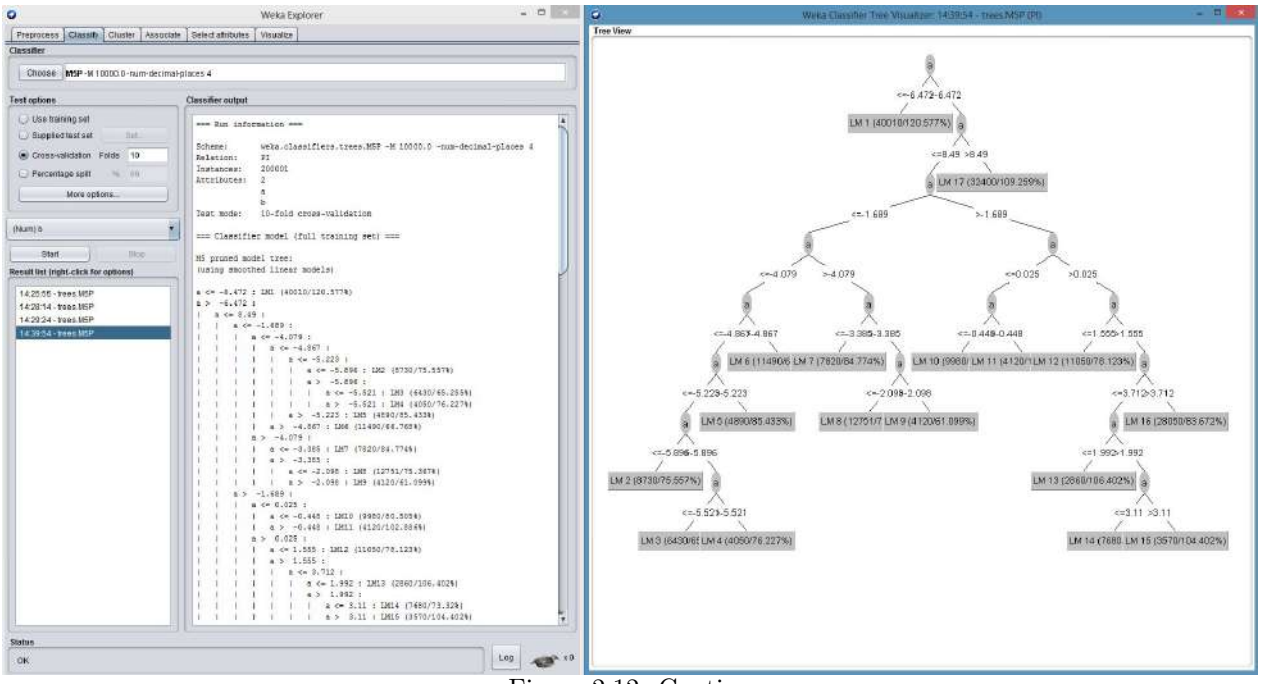


Figure 2.12: Caption

1. **Data Preparation and Formatting:**
   The dataset was first prepared in a structured format suitable for supervised learning. Input and output variables were selected based on the modeling objective (e.g., MPPT control, power forecasting). The dataset was saved in a WEKA-compatible format, either as a `.ARFF` file (Attribute-Relation File Format) or `.CSV`.
2. **Launching the WEKA Explorer Interface:**
   WEKA was launched, and the *Explorer* interface was selected to facilitate the modeling process. This interface provides access to key functionalities including preprocessing, classification, regression, and evaluation.
3. **Loading the Dataset:**
   Within the *Preprocess* tab, the dataset file was loaded. WEKA automatically parses the data and provides a summary of attributes, including types (numeric or nominal), missing values, and statistical summaries. At this stage, data normalization or filtering can also be applied using WEKA's preprocessing tools.
4. **Selecting the M5P Algorithm:**
   After preprocessing, the *Classify* tab was opened. From the list of available regression algorithms under `trees`, the **M5P** model was selected. WEKA allows configuration of M5P options, including:
   - Minimum number of instances per leaf
   - Use of pruning
   - Use of smoothing
   - Option to build unpruned models
5. **Setting the Target Variable:**
   The target (dependent) variable was selected from the dataset attributes (typically the output power, voltage, current, or tracking efficiency in energy applications).
6. **Model Training and Validation:**
   Cross-validation was selected as the model evaluation strategy, commonly using 10-fold cross-validation. WEKA then trained the M5P model on the dataset, building the model tree and generating local linear regressions at the leaves.
7. **Evaluating Model Performance:**
   Once training was complete, WEKA displayed performance metrics such as:
   - Correlation coefficient
   - Mean Absolute Error (MAE)
   - Root Mean Squared Error (RMSE)
   - Relative Absolute Error (RAE)
   - Model tree structure with decision rules and linear models
8. **Model Interpretation and Exporting Results:**
   The structure of the generated M5P model was examined for interpretability and relevance. Decision splits and leaf equations were documented. Additionally, the model or its predictions could be saved or exported for further analysis or integration into a control algorithm.
9. **Fine-Tuning and Reiteration:**
   Based on performance metrics, M5P parameters (such as pruning options or min-

imum instance thresholds) were adjusted, and the training process was repeated until optimal accuracy and generalization were achieved.

This structured methodology ensured the generation of an interpretable, accurate, and computationally efficient M5P model using WEKA for energy control applications.

Chapter 3

Optimizing Solar Power System: Advanced Maximum Power Point Tracking

3.1 Introduction

In recent years, solar energy has become more attractive as a renewable energy choice in both commercial and academic settings. This is mostly due to the challenges associated with conventional fossil fuel energy sources. The existence of oil production monopolies in some countries, disputes over oil resources, ecological pollution, and the increasing annual energy consumption rate have emphasised the need for alternative energy sources. Solar energy is a prominent kind of sustainable energy due to its capacity as a reliable and eco-friendly power supply [94][103]. Despite the numerous challenges associated with solar energy, such as the production costs of solar panels, the complex installation process, limited operating lifespan, and decommissioning issues, efforts are continually made to reduce costs and enhance efficiency. To minimize the costs of solar panels, various Maximum Power Point Tracking (MPPT) approaches have been applied. To improve and increase the efficiency of photovoltaic (PV) systems under varying conditions (irradiation and temperature), several methods can be employed, such as MPPT techniques and enhancing PV materials. However, developing efficient MPPT algorithms remains the most economically viable option [15]. The performance of PV systems can be significantly boosted through the selection of an effective MPPT strategy and proper adjustment of the DC/DC converter [119]. A solar charge regulator using the usual perturbation and observation ($P\&O$) technique was introduced and evaluated in [133] with a power output of 200 W from the photovoltaic (PV) panels. A DC-DC converter is utilized in solar power systems to amplify the power output of photovoltaic (PV) panels. In [31], A buck-boost converter was used together with a ($P\&O$) method, to optimize the energy generation of PV system panels.
The constant voltage method is another technique capable of tracking the Maximum Power Point (MPP) [48], It offers fast tracking, a simple structure, and implementation flexibility; however, significant ripples and large error values reduce system accuracy. The incremental conductance approach is used in literature [136]. Although the incre-

mental conductance method achieves satisfactory convergence tracking [136], the use of a set step size leads to extra oscillations during maximum power point (MPP) operation. This prolongs the tracking time and reduces the performance of the solar cell. To overcome the limitations of fixed step size increments, recent research has proposed the use of changeable step size in the incremental conductance technique [43]. However, this approach necessitates adjusting the slope of the PV panel in order to modify the step size, and it also requires manual calibration based on the level of irradiance. These factors pose challenges to the practical implementation of this method. A new variant is introduced in [114] [106], which incorporates an independent scaling factor and changes in slope angle. A new variant was presented in [27] that incorporates an independent factor of scaling and changes in slope angle. In addition, the researchers tested several conventional and soft-determining MPPT approaches for photovoltaic panels using Converters with High Step-Up to establish the most efficient duty cycle. A literature review also introduces an MPPT strategy that utilizes a predictive control mechanism. Although predictive control demonstrates satisfactory performance, its intricate algorithmic structure and lengthy computational duration render it inappropriate for promptly adapting to abrupt variations in atmospheric variables, such as changes in irradiance and temperature [2] [101]. Traditional MPPT methods in solar systems face challenges connected to dynamic and environmental conditions. They often struggle to efficiently track the MPP under rapidly varying irradiance and temperature [34]. Also, partial shading can make multiple local maxima, making it hard for these techniques to determine the global MPP. Developed models that handle these problems generally improve system complexity and cost, determining their practicality in smaller or cost-sensitive applications. Furthermore, many traditional methods show slow convergence, decreasing overall system efficiency during environmental changes. Hardware constraints also restrict adaptability, as these techniques often depend on specific designs, hindering their versatility throughout diverse solar system configurations. Recent advancements in MPPT techniques have presented creative approaches to avoid the constraints of traditional techniques, leveraging modern computational and control technologies. Machine learning and artificial intelligence, including neural networks and reinforcement learning, allow real-time and highly adaptive MPPT, even under complicated scenarios like partial shading. Metaheuristic models such as particle swarm optimization, genetic algorithms, and grey wolf optimization excel in determining the global maximum in non-linear and multi-peak conditions. Hybrid methods, combining traditional techniques like $P\&O$ [97] or incremental conductance with developed techniques such as fuzzy logic or metaheuristics [17], enhance efficiency while maintaining simplicity. Adaptive and predictive control techniques [102] dynamically adapt to environmental variations or forecast conditions for proactive tracking. Furthermore, bio-inspired models, such as ant colony optimization and artificial bee colony, offer more rapid convergence and improved accuracy. The integration of IoT further allows real-time observation and centralized optimization, while developed energy management methods optimize system-wide performance by incorporating energy storage and grid interaction. Together, these improvements especially improve MPPT efficiency, adaptability, and reliability in diverse operating conditions. The motivation for choosing the proposed (FLC) in the MPPT method for PV systems is its special power to regulate nonlinearities, uncertainties, and dynamic environmental conditions inherent in photovoltaic systems. Unlike traditional MPPT techniques,

FLC does not need a specific mathematical model, making it highly robust and effective under variable irradiance and temperature. Its rule-based structure, grounded in expert knowledge, facilitates implementation while guaranteeing adaptability to rapidly varying conditions without the demand for frequent retuning. In addition, FLC reduces steady-state oscillations around the MPP, resulting in softer and quicker convergence, which improves the general energy harvesting efficiency. It is also flexible to noise and sensor inaccuracies, providing reliable performance even in disturbances. These features render the FLC algorithm an ideal option for stand-alone PV systems, where stability, efficiency, and reliability are essential for possessing uninterrupted power delivery [105]. Rooted in human decision-making, FLC uses linguistic rules and membership functions, permitting it to respond adaptively to varying system conditions without needing tuning operations. This flexibility is one of its essential theoretical advantages, as it allows the controller to handle uncertainties and variations in system performance effectively. The aforementioned mixed attributes make FLC not only a theoretically sound option but also a highly adequate and practical solution for optimizing the energy harvesting abilities of stand-alone PV systems. The novelty of the proposed algorithm is in its adaptive rule-based approach, which enables precise and fast-tracking of the global MPP under different dynamic conditions and partial shading. It reduces steady-state ripples, enhances stability, and operates effectively across diverse configurations without depending on rigid models offering a robust solution for maximizing solar PV energy harvesting.

In this research, a new (MPPT) control constructed on a Fuzzy Logic Controller (FLC) algorithm is proposed to enhance the output efficiency of solar power systems. The motivation behind this work is to leverage the numerous advantages of FLC, including its exceptional adaptability and simplicity of use, its ability to simulate human-like reasoning, and its capability to construct non-linear functions. Developed with the guidance of experts, FLC allows for the application of flexible constraints and offers a highly effective approach for dealing with imprecise data [13]. The novelty of this work lies in the integration of FLC into the MPPT control, which dynamically adjusts to changing environmental conditions, ensuring rapid convergence to the MPP) without the need for a precise mathematical model. This innovative approach not only improves tracking speed and accuracy but also upgrades the robustness and reliability of the solar power system, contributing to the field by simplifying the control strategy and reducing implementation costs [30].

The theoretical advantages of the proposed FLC-MPPT algorithm including the addresses existing research gaps by tackling key limitations of conventional and advanced MPPT methods. It effectively addresses and avoids the challenge of slow convergence and inadequate performance under dynamic environmental conditions. The adaptive FLC determines the difficulty of tracking the global MPP in scenarios with partial shading. Besides, the method bridges the gap between simplicity and advanced performance by presenting a computationally efficient option for complex models like Particle Swarm Optimization (PSO) [81] or neural network (NN) [100] [104] algorithm, which need powerful computational resources or extensive training. It also manages the requirement for a versatile MPPT solution that can adjust to various PV system designs without depending on standard mathematical models. By enhancing tracking speed, accuracy, and adaptability, the proposed method provides a robust and practical solution

to improve energy efficiency in solar PV systems, filling critical voids in current MPPT research [67].

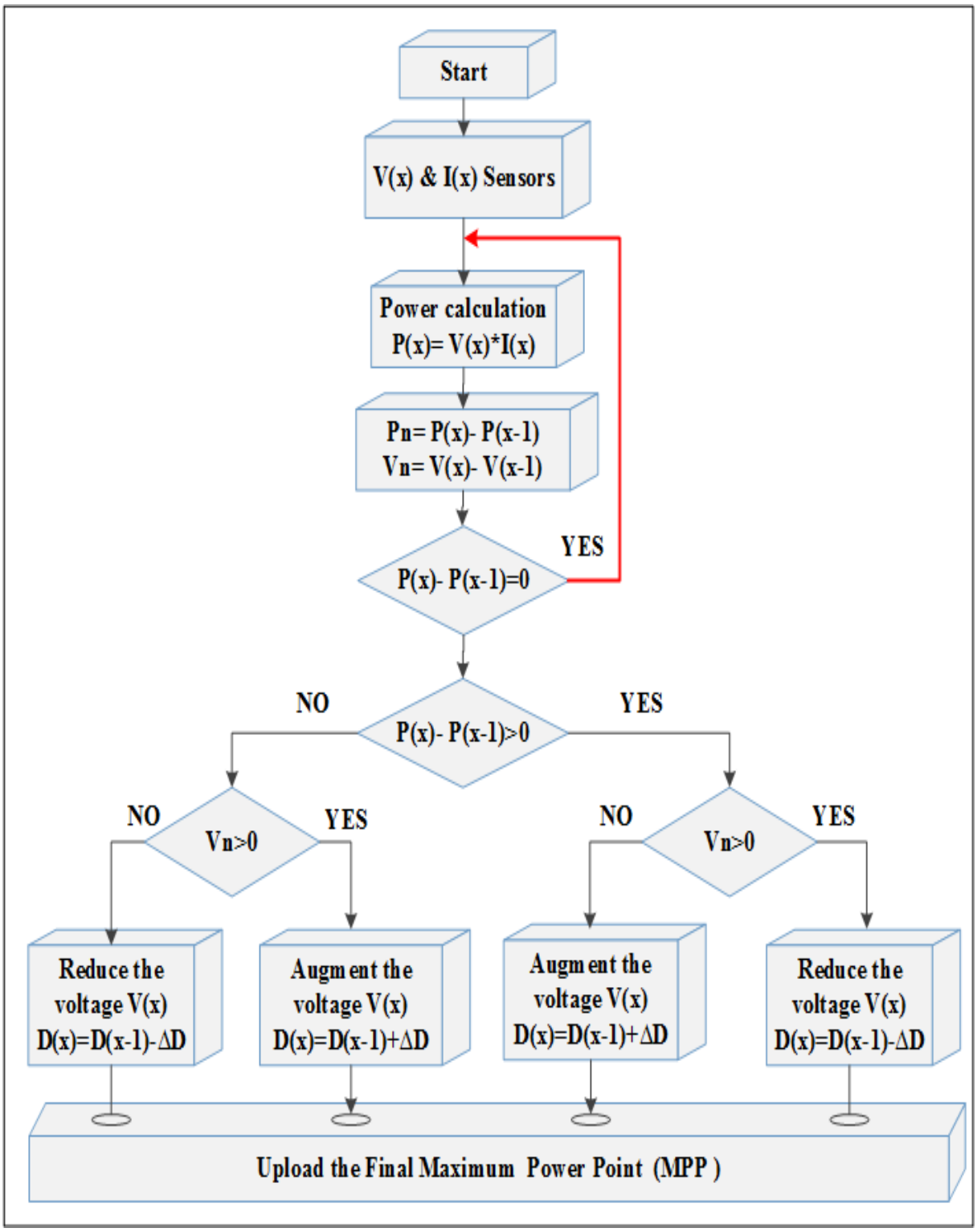


Figure 3.1: flowchart of MPPT strategy

Figure.3.1 illustrates the followed methodology to generate and mainain the proposed FLC algorithm.

3.2 PV system Modeling

3.2.1 Equivalent Circuit of PV Cell

Figure 3.2 displays the detailed configuration of the PV cell circuit. It consists of four electrical components: a series resistance (Rs), a current source, a diode linked in parallel with the current source, and a parallel resistance (Rsh) [137]. The diode current and the PV voltage may be determined by using the Kirchhoff Current Law (KCL) as described in reference [72]. The Rp value has a much higher magnitude when compared to the Rse value [93]. There are two kinds of installations available for the photographic system: PV stand-alone installation and solar power system linked to the grid. Figure 2 depicts a detailed scheme of a PV cell, that involves a parallel resistor and diode [118]. The PV

Table 3.1: Specification parameters of the experimental PV system and DC/DC converter

Parameter of PV Panel		**Parameter of DC/DC Converter**	
Number of PV panel	1 panel	Input capacitor (C1)	1000 µF
Max Power (P_{max})	200 W	Inductor (L)	10 mH
Max current (I_{mp})	4.26 A	Output capacitor (C2)	1100 µF
Max Voltage (V_{mp})	47.06 V	Switching Frequency	20 kHz
Open Circuit Voltage (V_{oc})	57.6 V	Load resistor (R_{Load})	495.5 Ω
Short Circuit Current (I_{sc})	4.6 A		
Working Temperature	-45° to +85°C		

panel number (1 panel) defines the system's modularity, while the maximum power (200 W) represents the panel's peak outcome under standard test conditions. The maximum current (4.26 A) and maximum voltage (47.06 V) display the optimal operating points for reaching maximum power [135]. The open-circuit voltage (57.6 V) and short-circuit current (4.6 A) are required to understand the panel's electrical limits and provide compatibility with other components. Finally, the working temperature range (-45°C to +85°C) spotlights the system's durability and adaptability to powerful environmental conditions, guaranteeing dependable operation in various climates [122].

Figure.3.4. Illustrates the realistic technical specification of solar panel parameters.

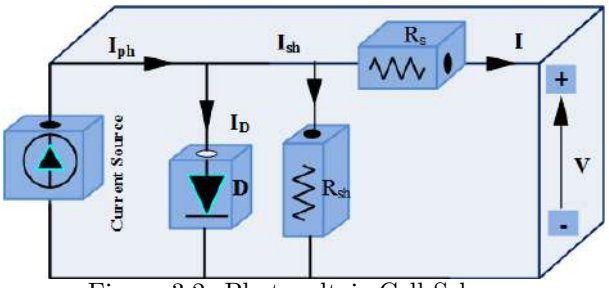


Figure 3.2: Photovoltaic Cell Scheme

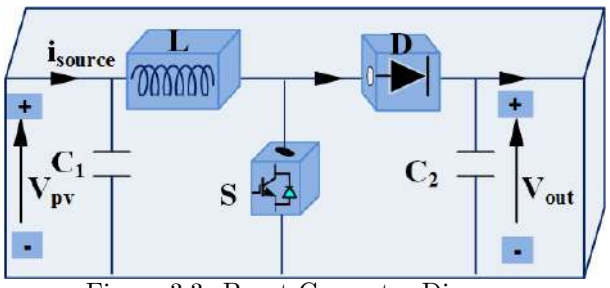


Figure 3.3: Boost Converter Diagram

The parameters of table 3.1 are used according to the label provided by the solar panel manufacturer, as shown in the figure below: (Technical Specification). The mathemat-

ical relation which explains the interaction between the output voltage and current is represented by the next equations:

$$I = I_{ph} - I_D - I_{sh} \tag{3.1}$$

$$I_{ph} = \frac{G}{1000}\left[I_{sc} + \mu(T - T_r)\right] \tag{3.2}$$

$$I_D = I_0\left[\exp\left(\frac{q(V + R_s I)}{nKT}\right) - 1\right] \tag{3.3}$$

$$I_{sh} = \frac{V + R_s I}{R_{sh}} \tag{3.4}$$

$$I_0 = \frac{I_{sc} \cdot T^3 \cdot \exp\left(-\frac{qE_g}{KT}\right)}{\left(\exp\left(\frac{qV_{oc}}{nKT_r}\right) - 1\right) \cdot T_r^3 \cdot \exp\left(-\frac{qE_{gr}}{KT_r}\right)} \tag{3.5}$$

$$E_g = E_{g0}\left(\frac{\alpha T^2}{\beta + T}\right) \tag{3.6}$$

Where q is the charge of the electron ($1.602x10^{-19}C$), K is the constant of Boltzmann ($1.381 * 10^{-23}J/K$), I_s (A) is the current of reverse saturation Tc is the temperature of the photovoltaic device (Kelvin) and N is the diode quality factor[133]. In PV systems, series resistance R_s limits current discharge, decreasing efficiency and the fill factor, while shunt resistance Rsh induces leakage currents, reducing voltage and power output. Minimum values of R_s and maximum values of R_{Sh} are critical for optimal performance. Determination of R_s and R_{sh}:By examining the current-voltage (I-V) curve of a PV cell: The incline of the I-V curve close to the short-circuit current (Isc) point is affected by R_s, which uses the following formula:

$$R_s = -\left(\frac{dV}{dI}\right)_{\text{near } I_{sc}} \tag{3.7}$$

While the slope of the I-V curve close to the open-circuit voltage V_OC is affected by R_{sh}, used as follows:

$$R_{sh} = -\left(\frac{dV}{dI}\right)_{\text{near } V_{oc}} \tag{3.8}$$

In a PV cell, (R_s) denotes inner resistive losses generated by the material, connections, and interconnections, significantly decreasing the output voltage, power, and efficiency under high current requirements. Ideally, R_s should be minimised to improve performance. On the other hand, (R_{sh}) accounts for leakage currents via flaws or impurities, which avoid the load and decrease the cell's output current and power. A high Rsh is desirable to reduce these losses and support the efficiency range, especially at low irradiance levels. R_s and R_{sh} affect the fill factor, efficiency, and general performance of the PV cell. Modules in series connection are linked in series to raise the voltage while keeping the same current. A collapse in one module impacts the whole string. Modules in parallel connection are linked in parallel to boost the current while keeping the same voltage. If one module fails, the others can still function.

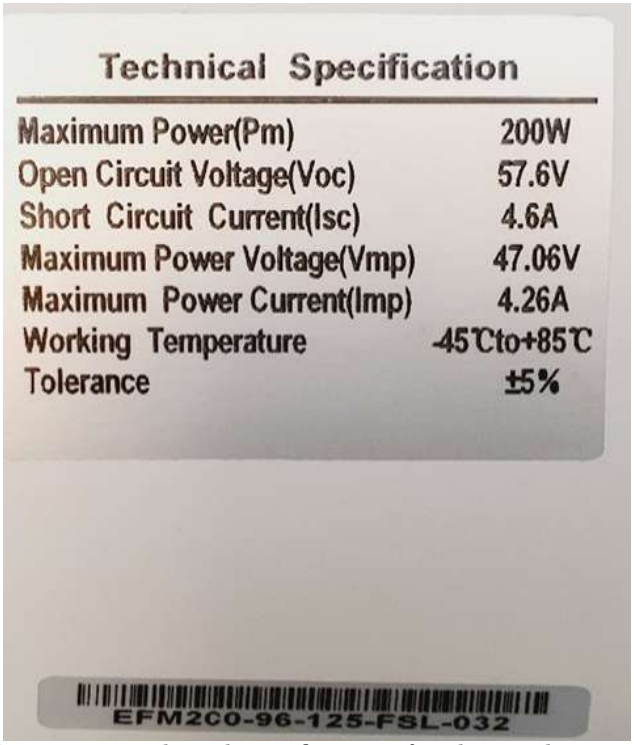


Figure 3.4: Technical specification of realistic solar panel

3.2.2 DC/DC Converter

A DC/DC converter is an apparatus that accumulates input energy to transform direct current across one voltage level into another[75]. The fundamental elements used in this current subject are an input capacitor (C_1), an inductor (L), a semiconductor IGBT/DIODE, a diode, and an output capacitor (C_2) as seen in Figure 3.3. Table III displays the values employed in the boost of the converter. To achieve the increased output value of the DC converter shown in Figure 4, there are two operational modes:

- When switch S is closed and switch D is open, the input energy flows through the inductor L, and the diode is in a reverse-bias condition. As a result, no current flows through the diode. However, the input voltage passing through switch S is applied to the load, causing the output voltage to increase.
- When switch D is closed and switch S is open, the stored energy in the inductor L is released, further increasing the output voltage of the boost converter. A comprehensive analysis was conducted on the DC/DC converter in reference [14] [112].

The parameters in Table 2 illustrate the essential elements of the boost converter, providing an efficient and stable process in the proposed PV system. The output capacitor ($C_1 = 1100 \text{ţ} F$) is fixed to reduce output voltage ripple and keep a steady DC voltage for the load. The inductor (L=10 mH) is sized to store and transmit energy effectively while decreasing current ripple during the boost process. Lastly, the input capacitor ($C_1 = 2000 \text{ţ} F$) is determined to stabilize the input voltage by filtering out high-frequency noise and oscillations from the PV panel. These components are set to optimize the converter's performance, guaranteeing reliable energy transfer and voltage

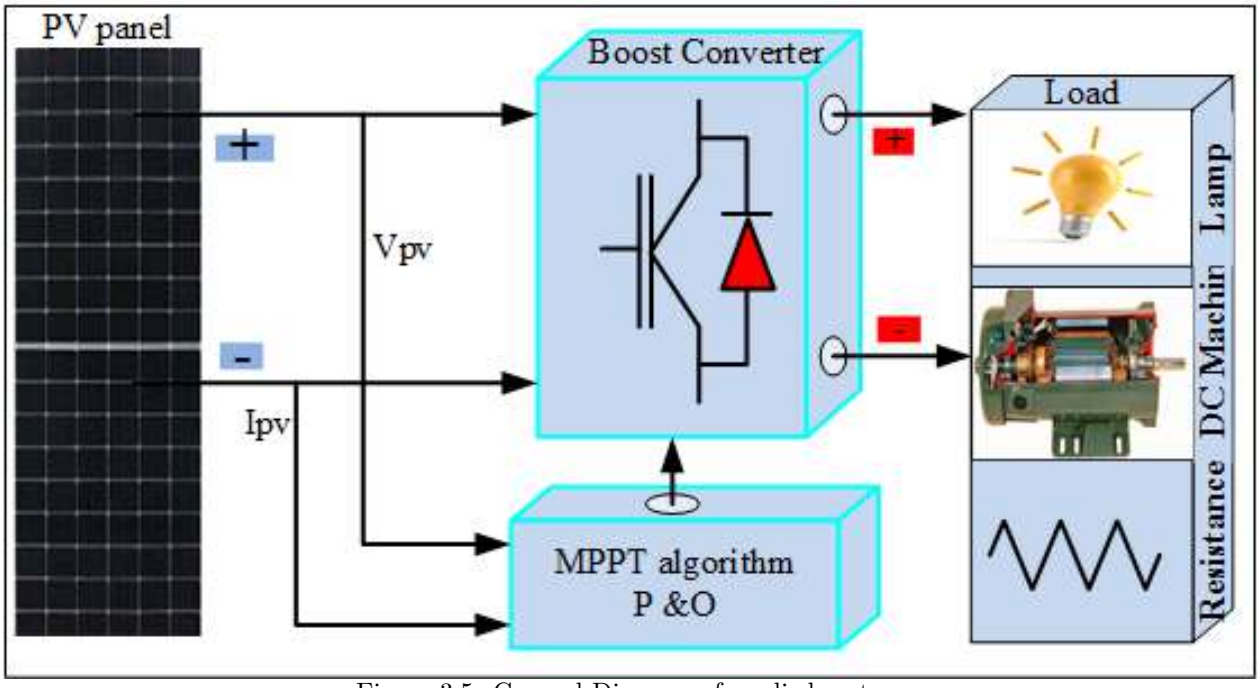


Figure 3.5: General Diagram of applied system

regulation [112]. According to the given values of input and output voltages of boost converter, switching frequency fs and load current Iload,V_{in} = 51v V,V_{out}= 100 V, f_s = 20kHz, I_{load} = 0.125A. Ripple current ΔI_{Load} 10%= 0.0125 A, ripple voltage ΔV_{out}=0.1 V, the parameters of the boost converter are calculated as follows:

- Calculation of inductor L:

$$L \geq \frac{V_{\text{in}} \cdot (V_{\text{out}} - V_{\text{in}})}{\Delta I_{\text{load}} \cdot f_s \cdot V_{\text{out}}} \Rightarrow L \geq \frac{51 \cdot (100 - 51)}{0.0125 \cdot 20000 \cdot 100} \Rightarrow L \geq 10\,\text{mH}$$

- Calculation of output capacitor C_2:

$$C_2 \geq \frac{I_{\text{load}}}{8 \cdot f_s \cdot \Delta V_{\text{out}}} \Rightarrow C_2 \geq \frac{0.125}{8 \cdot 20000 \cdot 0.1} \Rightarrow C_2 \geq 781.25\,\mu F$$

- Calculation of input capacitor C_1:

$$C_1 \geq \frac{\Delta I_{\text{load}}}{4 \cdot f_s \cdot \Delta V_{\text{in}}} \Rightarrow C_1 \geq \frac{0.0125}{4 \cdot 20000 \cdot 0.5} \Rightarrow C_1 \geq 312.5\,\mu F$$

The value of 2000 F is adequate to address the stability of input voltage and raise the filtering process [144]. The aforementioned values in Table II are realistic values that align with the experimental process in our work. The boost converter operates in two modes [132]:

- Continuous Conduction Mode (CCM): The inductor current never falls to zero in this mode. This process includes two sub-phases:

- When the switch IGBT is on, the inductor supplies energy as the current boosts linearly, and the diode is reverse-biased, isolating the load.
- When the switch is off, the inductor discharges its stored energy to the load via the diode, keeping the output voltage higher than the input voltage [4].

• Discontinuous Conduction Mode (DCM): In this mode, the inductor current descends to zero during part of the switching cycle. This happens at lighter loads or lower input voltages, causing a distinct third phase where no current flows via the inductor.

3.3 Maximum Power Point Tracking Strategy Based on Fuzzy Logic controller

In solar energy systems, Maximum Power Point Tracking (MPPT) is a critical topic due to its essential role in maximizing the generated solar energy. This paper presents an implementation of an MPPT strategy based on an intelligent Fuzzy Logic Controller (FLC) to enhance the performance of photovoltaic (PV) systems. Figure 5 illustrates the formation mechanism of the FLC algorithm through a detailed flowchart.
The MPPT idea is a crucial issue in solar energy systems because it plays an essential role in maximizing the amount of solar energy generated [16] [113]. This study implements a Maximum Power Point Tracking (MPPT) system using an artificially intelligent Fuzzy Logic Controller (FLC) to improve the performance of the Photovoltaic (PV) system. Figure 3.6 is a flowchart that demonstrates the formation method of the FLC technique. Traditional MPPT algorithms are encountering a significant obstacle in effectively managing waste energy due to steady state settings and inadequate dynamic performance resulting from sudden fluctuations in irradiance and temperature [58]. These challenges need us to study a sophisticated algorithm capable of overcoming major flaws and exhibiting a prompt adaptive response to sudden variations in climatic circumstances. A study of the MPPT-FLC algorithm has been conducted in this discussion. Figure 3.7 depicts the Fuzzy Logic Controller (FLC) flowchart together with its two inputs, namely the error (E), the derived error (ΔE), and its output, the duty cycle (D).

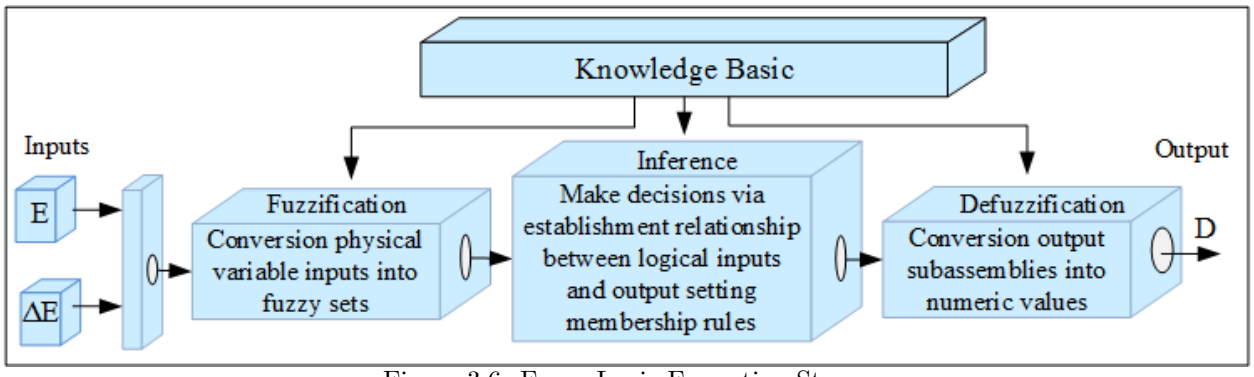


Figure 3.6: Fuzzy Logic Formation Stages

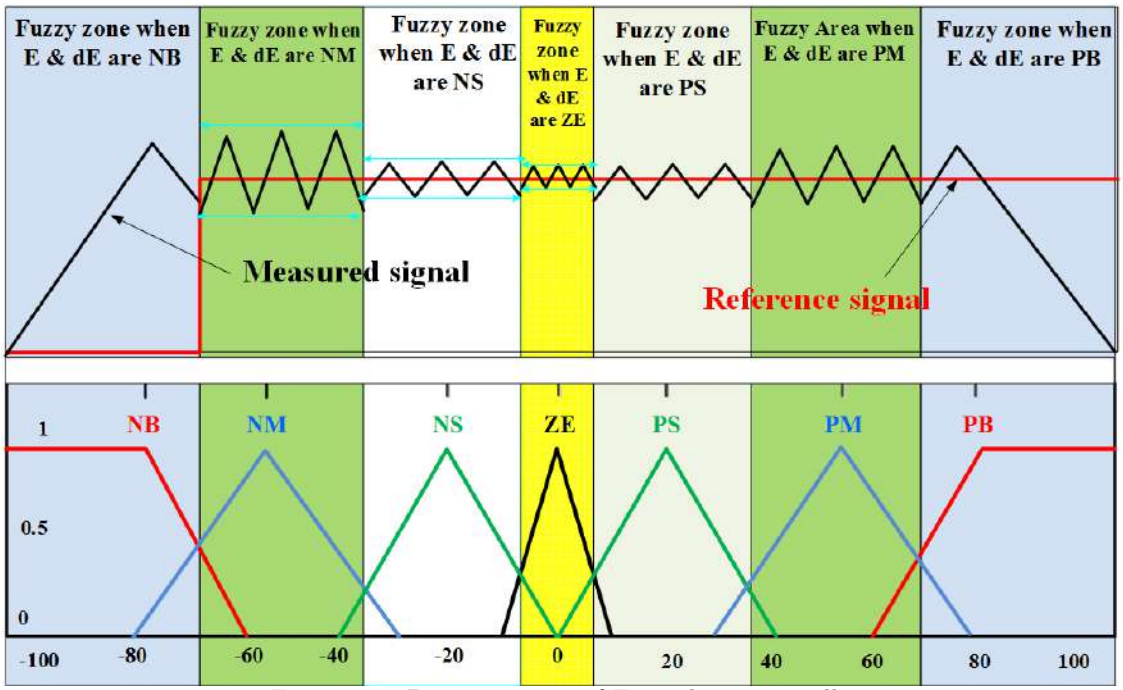


Figure 3.7: Design system of Fuzzy logic controller

3.3.1 Proposed FLC Algorithm Design

In order to design the fuzzy logic based on the MPPT strategy, six steps are followed for the fuzzy design mechanism:

- Define Input and Output Variables: Error and derivative Error are the input variables and are given as follows:

$$E_p = A = P^* - P_{\text{mes}} \tag{3.9}$$

$$\Delta E_p = \Delta E_p(k) - \Delta E_p(k-1) \tag{3.10}$$

The nature of E corresponds with rule-based fuzzy logic (if-then), enabling intuitive and efficient control. Therefore, these inputs supply a proportion of accuracy, responsiveness, and computational efficiency for a robust MPPT strategy. Error is described as the difference between the actual power and the reference power, defining how far the system is from the maximum power point (MPP). The derivative error captures the rate of evolution of error over time. The output, duty cycle (D), defines the adjustment to the PWM signal to align the operating point with the MPP. The error (E) and derivative error ΔE are selected as inputs of the FLC algorithm based on their ability to manage the system's operational condition and dynamics comprehensively. Error (E) shows the deviation from the MPP, supplying essential feedback for corrective actions, while ΔE reflects the rate of evolution of E, allowing predictive control and quicker convergence. This combination provides effective tracking under dynamic conditions, reduces power loss due to fluctuations, and stops overshooting. Besides, E and E together improve adaptability to the nonlinear attributes of photovoltaic (PV) systems and enhance response to quick environmental variations.

- Fuzzy Inputs and Output: The fuzzification methodology includes defining the input and output variables into linguistic terms. In our work, the linguistic variables have been simplified as follows: NB for Negative Big, NM for Negative Moyne, NS for Negative Small, ZE for Zone Zero, PB for Positive Big, PM for Positive Moyne, and PS for Positive Small as shown in Figure 3.7 Triangular membership function shapes are assigned to each linguistic term to describe their degree of membership. The triangular functions draw the crisp input values into fuzzy sets, allowing the system to manage nonlinearities and uncertainties effectively.

- Construct the Rule Base: The essence of the FLC algorithm lies in its rule design, which links the relationship between the inputs and the output. Rules are made based on the system's performance and field knowledge. For example, when the error is big positive, the duty cycle should rise to move toward the MPP. Contrarily, when the error is big negative, the duty cycle should decline to reduce overshoot. If the error is small and the derivative error closes to zero, the duty cycle stays unchanged, meaning that the system is near the MPP as shown in Figure. 3.7.

- Defuzzification of the Output The FLC system transforms the fuzzy outputs derived from the rule base into a crisp value for the duty cycle via a technique called defuzzification. Common techniques contain the centroid of area (COA), where the output value is defined as the centre of gravity of the aggregated fuzzy set, or the bisector of area (BOA), which separates the area of the fuzzy set into two equal parts. This step guarantees that the output is actionable and can be used for the PWM for MPPT.

- Simulate and Optimize MATLAB/Simulink supplies an intuitive graphical interface and a large library of pre-built blocks, such as fuzzy logic controllers.

  Figure 3.8 presents the maintenance process of the proposed FLC method for maximum power point tracking (MPPT).

  Moreover, MATLAB/Simulink excels in managing dynamic simulations, critical for evaluating MPPT performance under changing solar irradiance and temperature requirements. Its robust analytic tools and advanced visualization abilities permit for in-depth investigation of system performance. Besides, MATLAB's toolbox, involving the Fuzzy Logic Toolbox and Optimization Toolbox, enables the design, optimization, and fine-tuning of fuzzy rules and membership functions. These features, combined with their overall use in academia and industry, make MATLAB/Simulink a highly dependable and versatile option for MPPT strategy design and validation. The fuzzy MPPT control is simulated in a software environment like MATLAB/Simulink to validate its performance. The rule base and membership functions are tested under variable circumstances of solar irradiance and temperature. Performance metrics such as tracking efficiency, response time, and ripple reduction are evaluated. Creating linguistic variables in fuzzy logic control is crucial for several reasons [47]. First, it allows for the translation of qualitative human expertise and reasoning into a mathematical framework, making the control system more intuitive and accessible. Linguistic variables facilitate the handling of imprecise and vague information, which is often encountered in real-world scenarios, enhancing the system's ability to adapt to varying conditions.

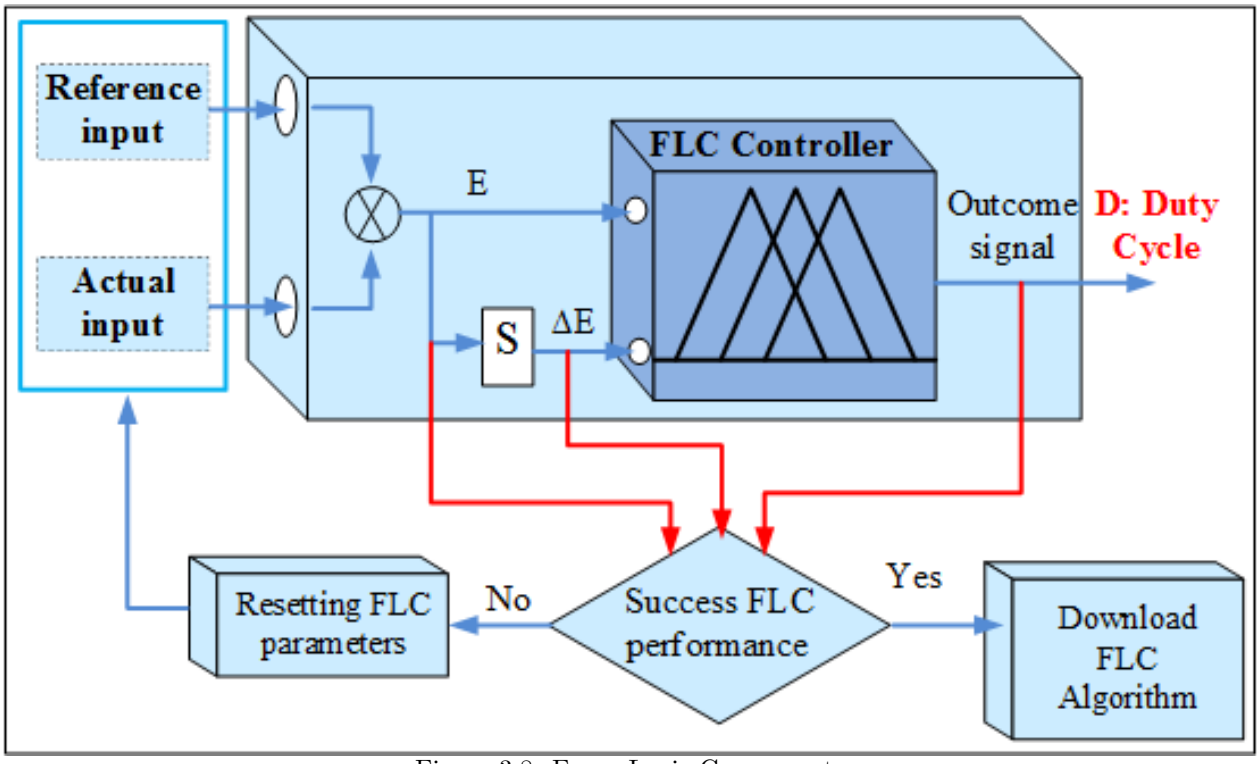


Figure 3.8: Fuzzy Logic Components

3.3.2 Scalability of the FLC Algorithm

The scalability of the proposed (FLC) algorithm makes it appropriate for different PV system designs involving large-scale applications. For small-scale systems, the algorithm uses a simplified rule base and fewer membership functions, providing low computational overhead. For large-scale PV systems, the FLC can be boosted by raising the number of rules and improving membership functions to adjust the complexity of larger arrays and their dynamic active conditions. Besides, the design of the FLC permits decentralized control, where multiple FLC units can be used in parallel to control different sections of the PV system. This method distributes the computational burden and improves the system's scalability while maintaining stability and responsiveness. Such adaptability provides the algorithm's applicability via a broad range of PV structures, from residential systems to utility-scale installations, without compromising performance or reliability.

The proposed FLC presents significant advantages for MPPT in PV systems, especially in dynamic environmental conditions. However, its implementation comes with specific limitations and trade-offs. One essential challenge is the increased computational complexity compared to traditional methods like *P&O* or IC methods. The fuzzy inference technique and defuzzification stages require more processing power, which could be a limitation for low-cost or resource-limited microcontrollers. Besides, the performance of FLC is highly dependent on the structure of its rule base and membership functions. Formulating an effective rule set often needs expert knowledge and can be time-consuming, with suboptimal configurations potentially decreasing efficiency. Moreover, FLC systems may need periodic tuning to adjust to varying system conditions or

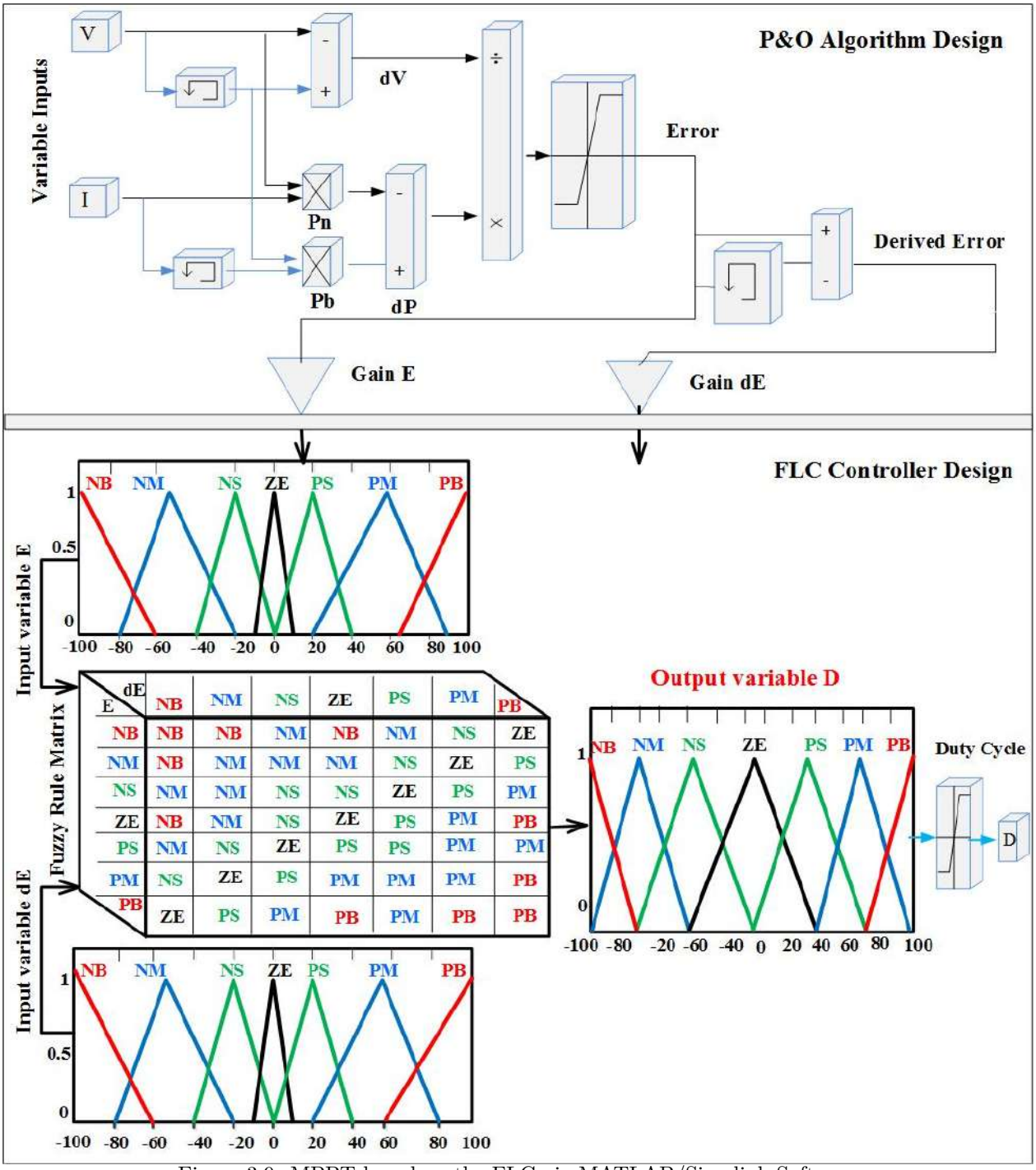


Figure 3.9: MPPT based on the FLC via MATLAB/Simulink Software

ageing PV modules, adding to maintenance efforts. Despite these challenges, advances in computational technologies and adaptive tuning methods restart to improve the feasibility of FLC, guaranteeing its viability for various solar applications.

3.4 Simulation Results

MATLAB/Simulink supplies an intuitive graphical interface and a large library of prebuilt blocks, such as fuzzy logic controllers. Moreover, MATLAB/Simulink excels in managing dynamic simulations, critical for evaluating MPPT performance under changing solar irradiance and temperature requirements. Its robust analytic tools and advanced visualization abilities permit for in-depth investigation of system performance. Besides, MATLAB's toolbox, involving the Fuzzy Logic Toolbox and Optimization Toolbox, enables the design, optimization, and fine-tuning of fuzzy rules and membership functions. These features, combined with their overall use in academia and industry, make MATLAB/Simulink a highly dependable and versatile option for MPPT strategy design and validation.
Figure 3.10 A and B show the MPPT zone. It can be seen that the MPPT zone keep the maximum points of voltage, current and power, which proves the effectiveness of the proposed FLC-MPPT algorithm.

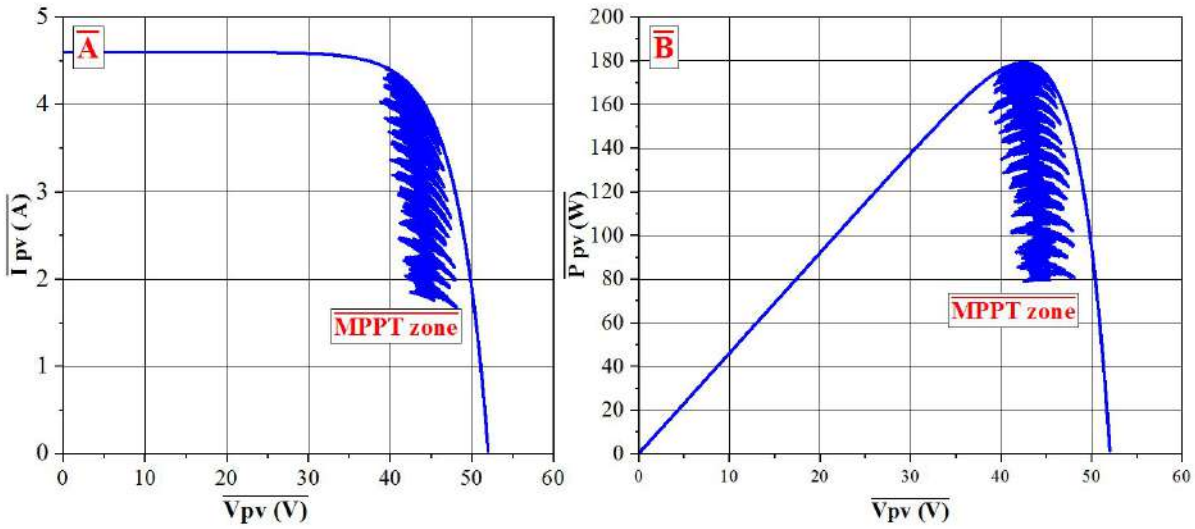


Figure 3.10: Characteristic curves P-V of MPPT technique

Figures 12 and 13 present comparative simulation results of the proposed FLC algorithm and the conventional $P\&O$ method. It can be seen that the proposed FLC algorithm achieved excellent performances free of the significant ripples, which proves the evectiveness of the proposed FLC algorithm.

At t = 4s, the irradiation reduces to 900 W/m^2, resulting in a corresponding adjustment in the output voltage and power of the boost converter. Also, at t = 7s, the irradiation rises to 1000 W/m^2 as shown in Figure 11. The system responds effectively by increasing the voltage and power levels of the boost converter. These quick and precise reactions to varying irradiation states indicate the FLC's capacity to track the

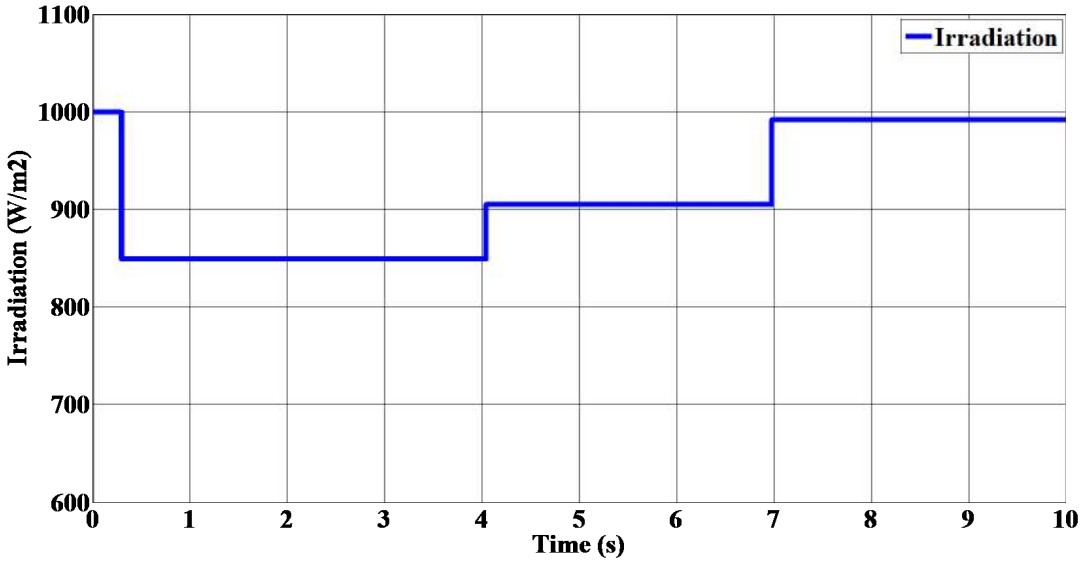


Figure 3.11: Irradiation profile for PV system

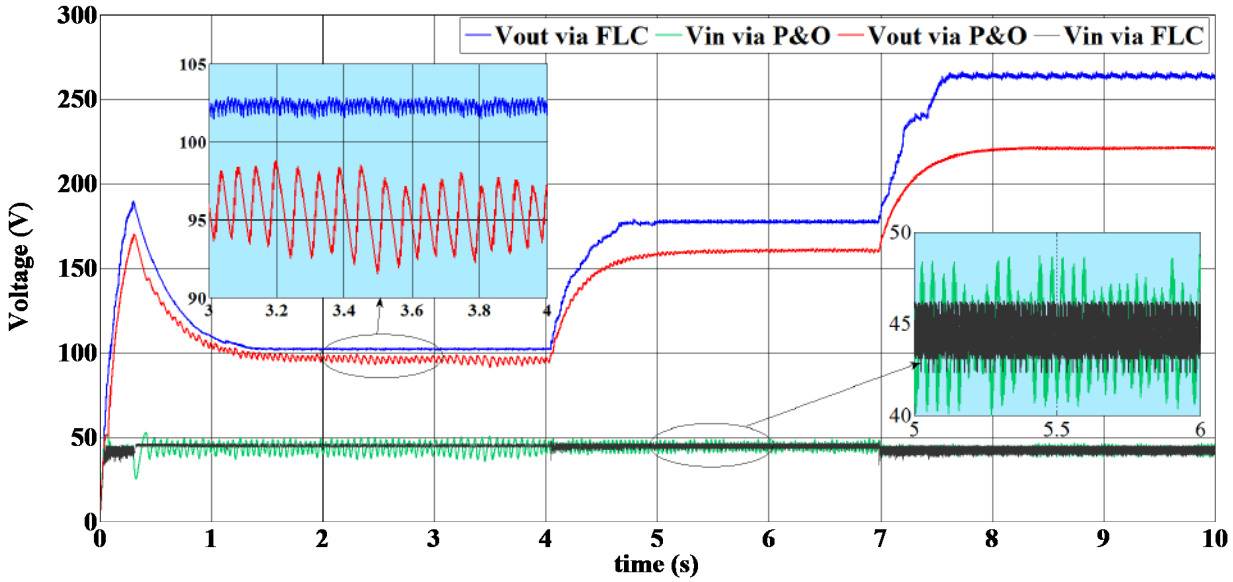


Figure 3.12: Boost converter input and output voltages

(MPP) efficiently. The FLC's adaptability stems from its ability to manage non-linear behaviours and dynamic changes in the PV system. Unlike conventional MPPT algorithms, such as ($P\&O$) or (IC), the FLC does not depend on fixed step sizes or linear decision-making. Instead, it employs a rule-based system to analyze changes in inputs (e.g., changes in irradiation) and outputs (e.g., voltage and power), allowing smoother transitions and quicker convergence to the MPP. Moreover, the FLC improves system performance by minimizing oscillations about the MPP and lowering energy losses during transient states [26]. This guarantees that the system is used optimally even under difficult conditions, such as rapidly varying irradiation levels. The sensitivity analysis emphasizes the robustness of FLC under extreme climatic conditions. Although there is

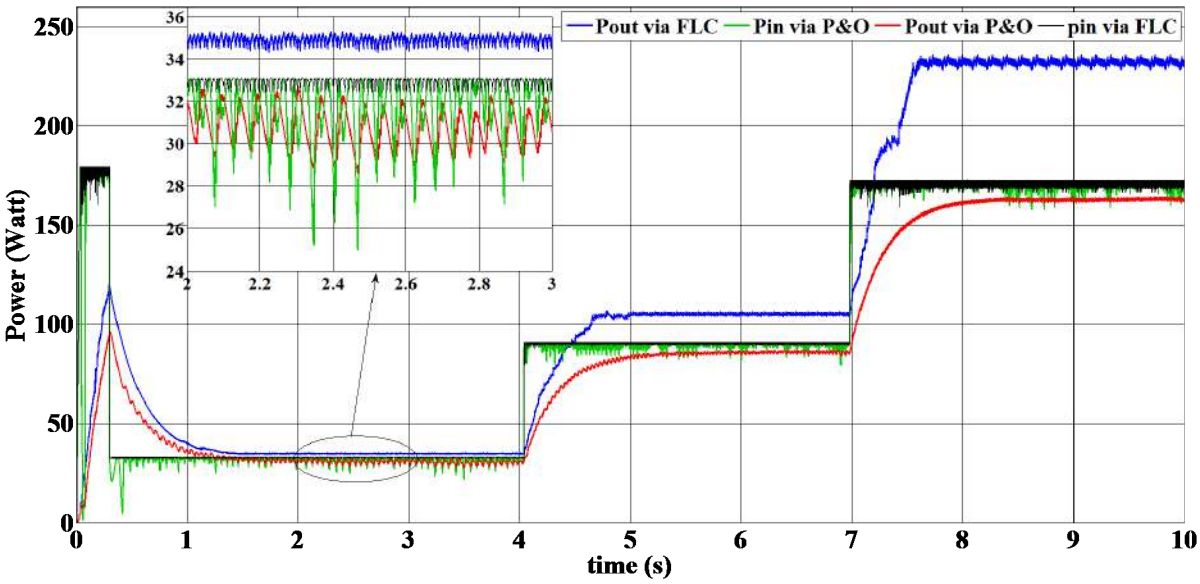


Figure 3.13: Input and output powers of the boost converter

a small degradation in performance, the controller restarts to operate effectively, keeping stability, efficiency, and adaptability. These outcomes prove that the FLC is well-suited for deployment in real-world PV systems where climatic variations are common. The practical platform for validating the performance of the offered (FLC) for the PV model was executed utilizing the setup illustrated in Figure 3.12 The following elements describe the calibration of equipment and test conditions:

- Equipment Calibration:

- Solar Panel: under standard test conditions (STC), the solar panel was tested to provide proper output characteristics as shown in Figure 3.

- Current and Voltage Sensors: The current and voltage sensors were calibrated via a reference multimeter (with an accuracy of $\pm 0.05\%$) to guarantee accurate voltage and current measures during experiments.

- Digital Multimeters: calibrated multimeters were utilised to calculate the boost converter's input and output voltages and currents. These devices conform to the IEC 61010 standard for measurement equipment.

3.5 Comparative Experimental Findings Based on $P\&O$ and FLC

In order to assess the results of the algorithm we have developed and showcase the usefulness of the outcomes, we carried out a three-minute experimental verification test using MATLAB software and DSpace 1103 hardware. Figure 3.14 depicts the fundamental equipment and instruments used in the experimental platform.

- Oscilloscope: The oscilloscope was calibrated by a reference signal generator to ensure correct waveform visualisation of the boost converter's input and output voltages.

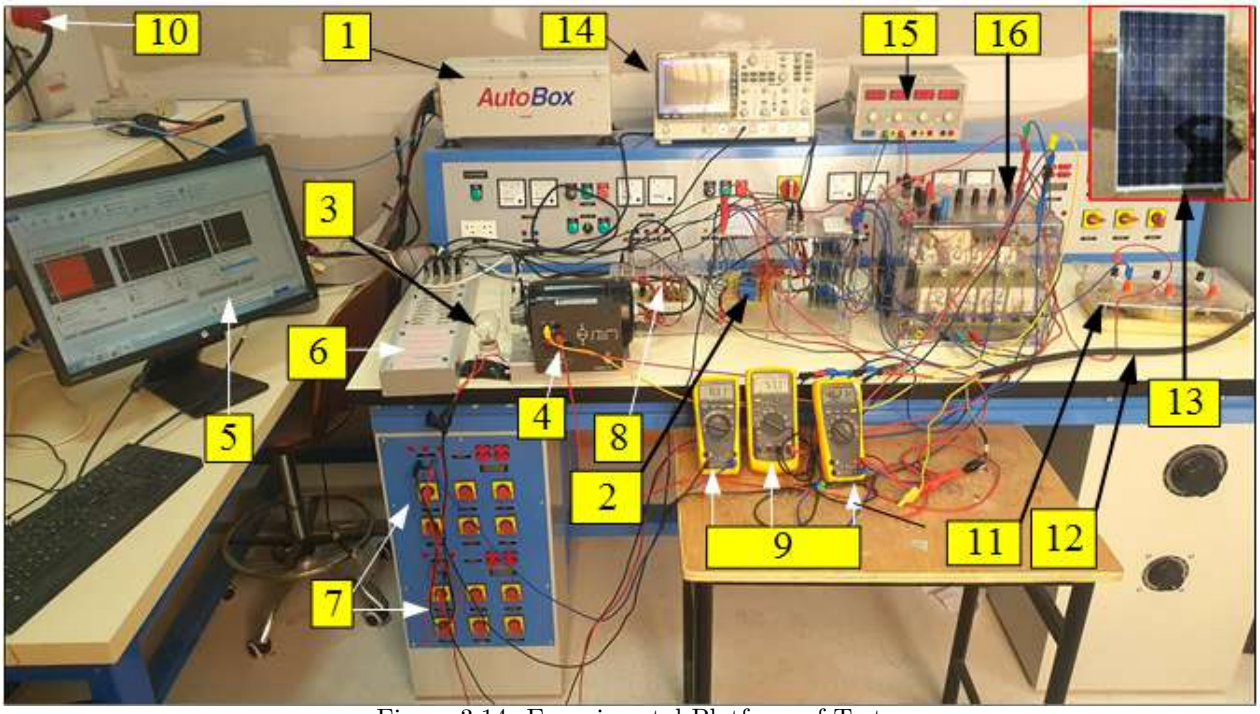


Figure 3.14: Experimental Platform of Test

- dSPACE 1103 Controller: The dSPACE system was configured and calibrated to communicate actually with the adaptive card, providing precise real-time data acquisition and control.
- Test Conditions:
- The experiments were conducted in a controlled laboratory environment, with ambient temperature and irradiation.
- Resistive and capacitive loads were used to simulate grid and battery storage integration. The loads were adjusted to analyze system performance under different operating conditions.

3.5.1 Experimental Results of MPPT Under Constant Resistive Load

The experiment included implementing the Maximum Power Point Tracking (MPPT) method using Fuzzy Logic Control (FLC) with a resistive load that remained constant throughout the experiment. Figures 3.16, 3.17, show the results of the proposed Maximum Power Point Tracking (MPPT) method for the voltage output of the solar panel (Vpv), the voltage output of the boost converter, and the power output of the boost converter, respectively. The FLC exhibited a smoother and less oscillatory performance, attributed to its capacity to effectively adjust to abrupt changes in air conditions.

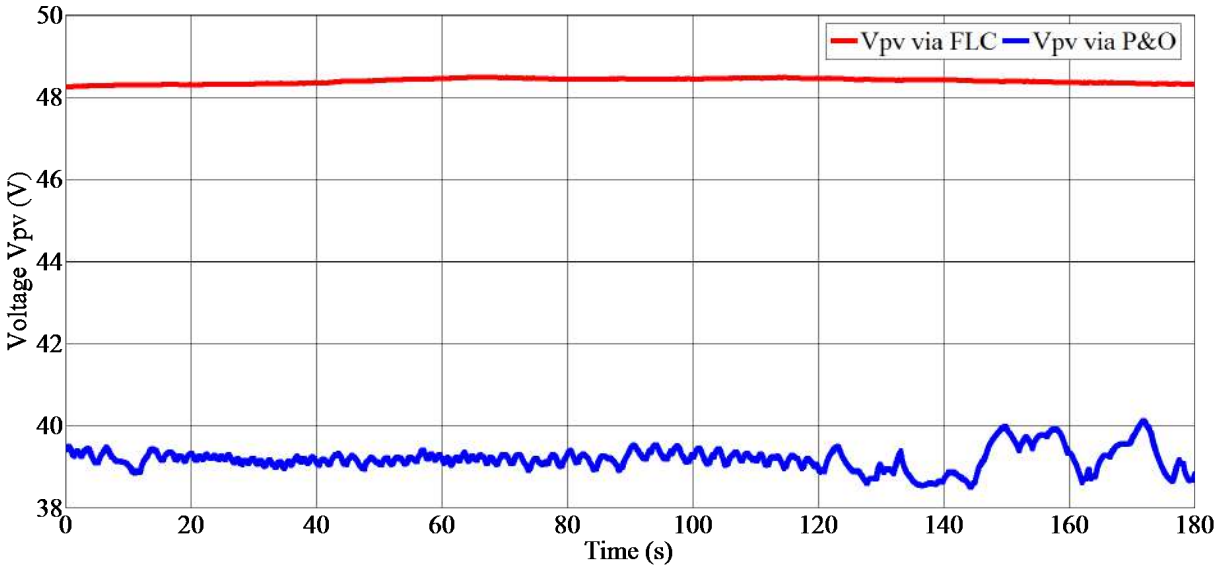


Figure 3.15: Solar panel output voltage

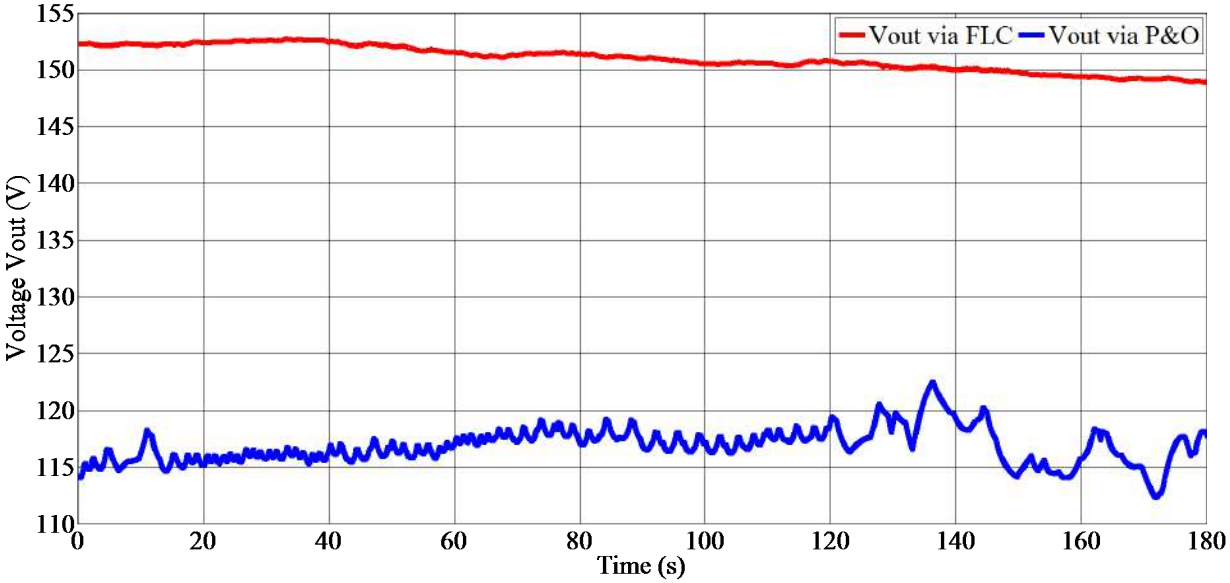


Figure 3.16: Boost Converter Output Voltage $V_{\text{out}}(V)$

3.5.2 MPPT Performance of FLC Algorithms Under Changeable Resistive Load

This experiment was conducted to evaluate the performance of the MPPT-FLC algorithm under fluctuating DC resistive load conditions at two different time intervals, namely at t=60 s and t=120 s. The objective of this experiment is to demonstrate the rapid responsiveness of the suggested algorithm under varying levels of workload. Figures 18, 19 and 20 depict the results of the input and voltage and power of the boost converter, respectively. It is worth mentioning that the FLC algorithm demonstrated higher efficiency, as seen in Figure 3.21, where the efficiency of the suggested method is

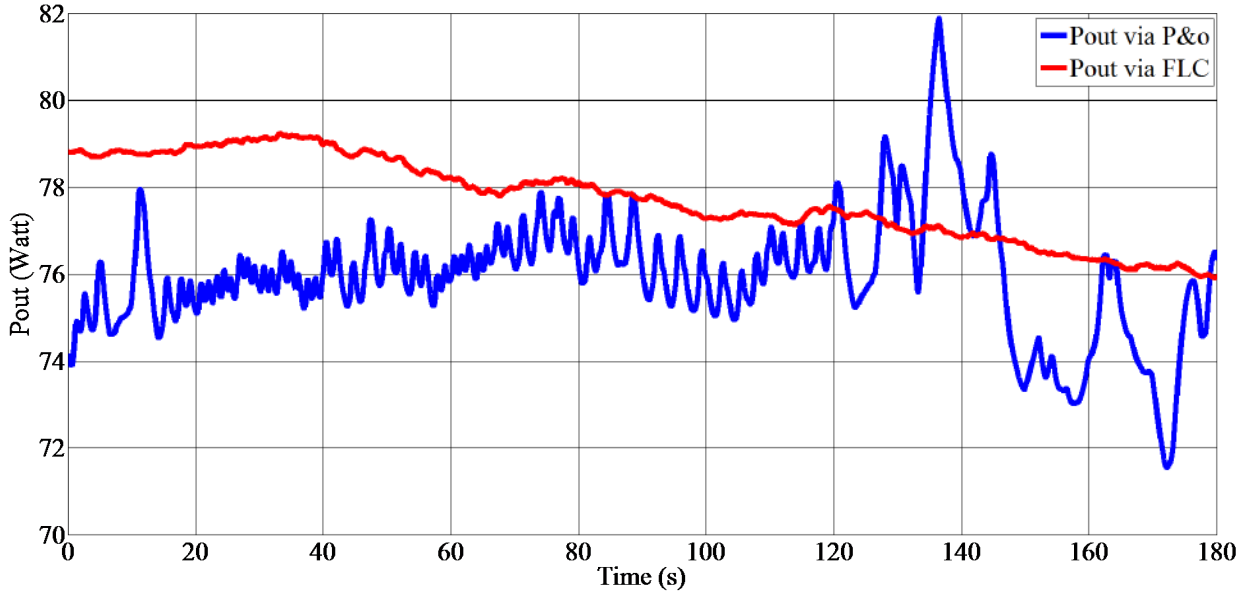


Figure 3.17: Boost Converter Output Power P (W)

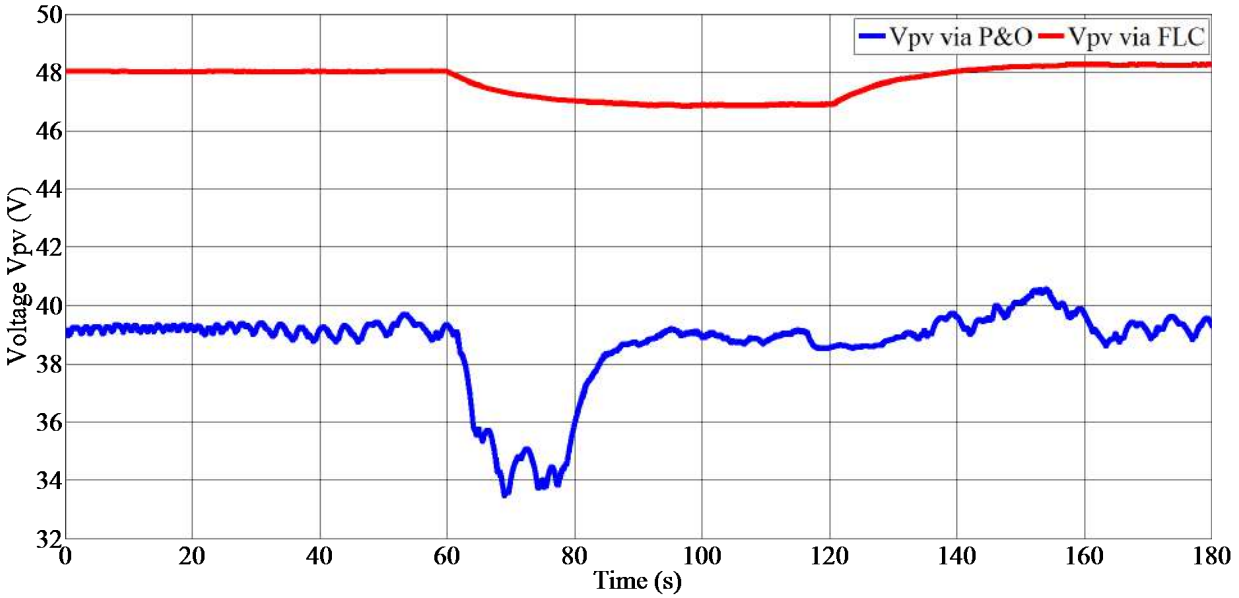


Figure 3.18: Boost Converter input Voltage with variable DC load.

around 0.83.

3.5.3 MPPT Strategy Performance Under DC Machine Load

This experiment was conducted to achieve the performance of the MPPT-FLC algorithm under fluctuating DC resistive load conditions at two different time intervals, namely at t=60 s and t=120 s. The objective of this experiment is to demonstrate the rapid responsiveness of the proposed approach under varying levels of workload. Figures 3.22, 3.23, and 3.24 depict the results of the input, output voltage and power of the boost converter, respectively. It is worth mentioning that the FLC algorithm demonstrated

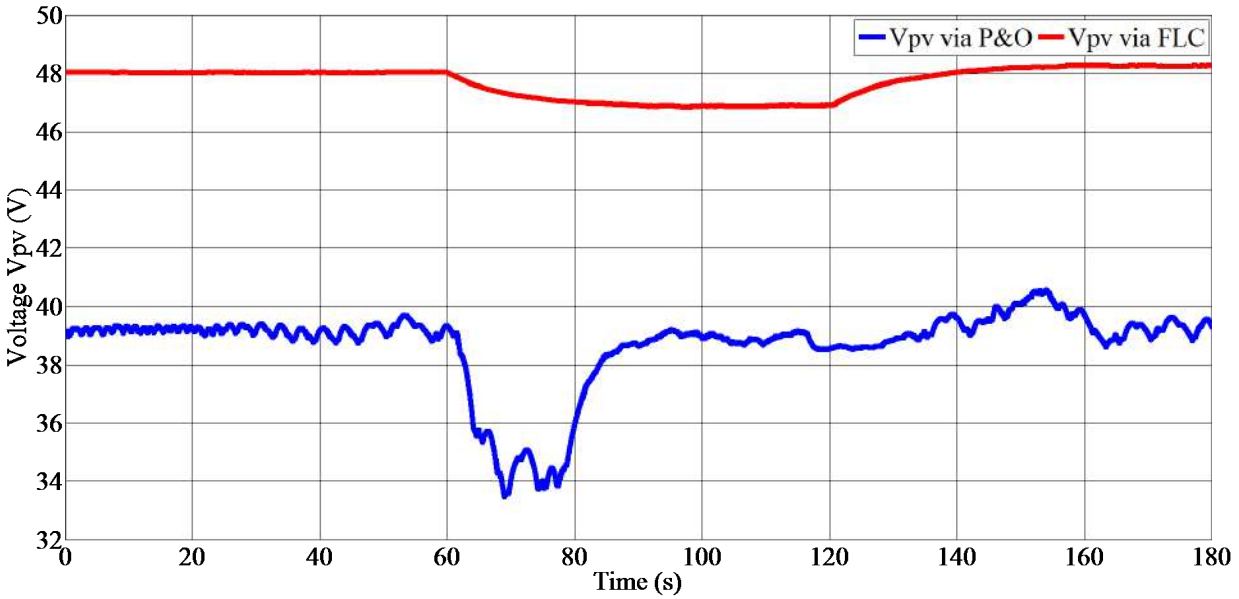


Figure 3.19: Boost Converter Output Voltage with variable DC load.

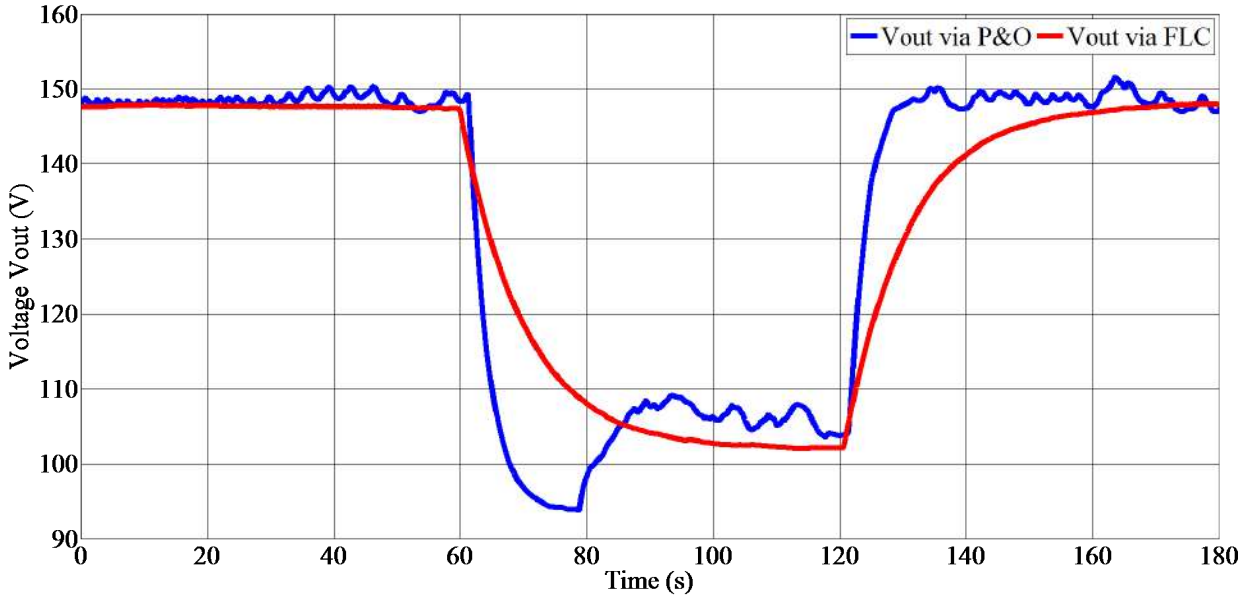


Figure 3.20: Boost Converter output power with variable DC load

higher efficiency, as seen in Figure 3.25, where the efficiency of the suggested method is around 0.83.

Figure. 3.26 presents experimental findings of the proposed MPPT algorithm. It can be seen that the FLC have a fast response to the sudden variations of load with high efficiency.

Key points from the experimental validation include:

- Real-time Implementation: The FLC-based MPPT algorithm was implemented in real time, demonstrating its practical applicability.
- Response Time: The system's response to changes in atmospheric conditions, such as

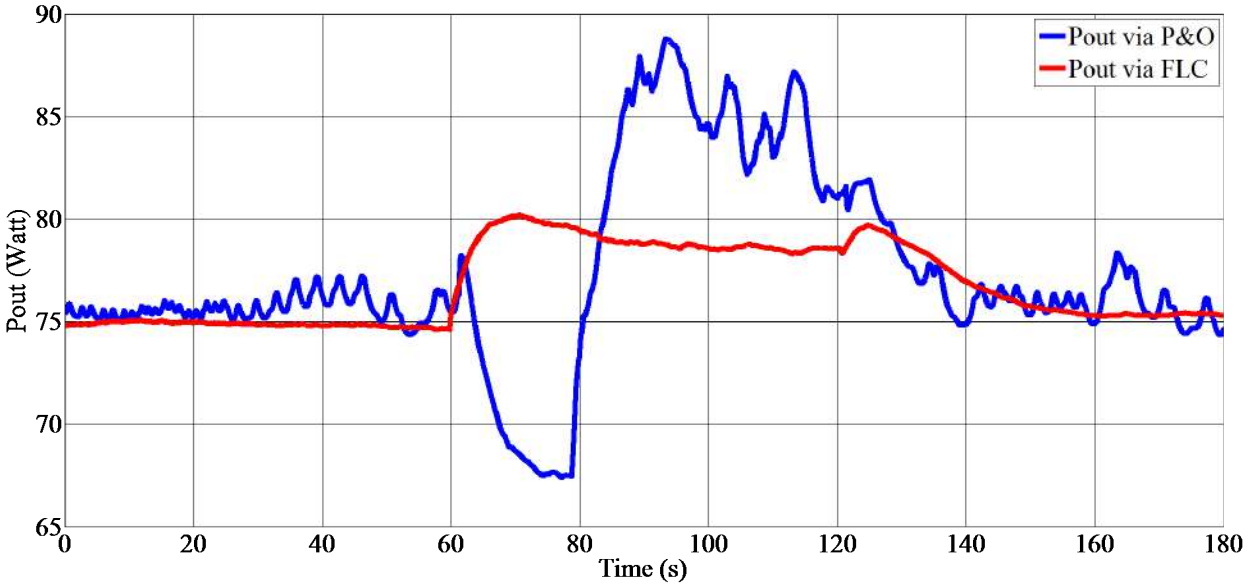


Figure 3.21: Boost Converter efficiency

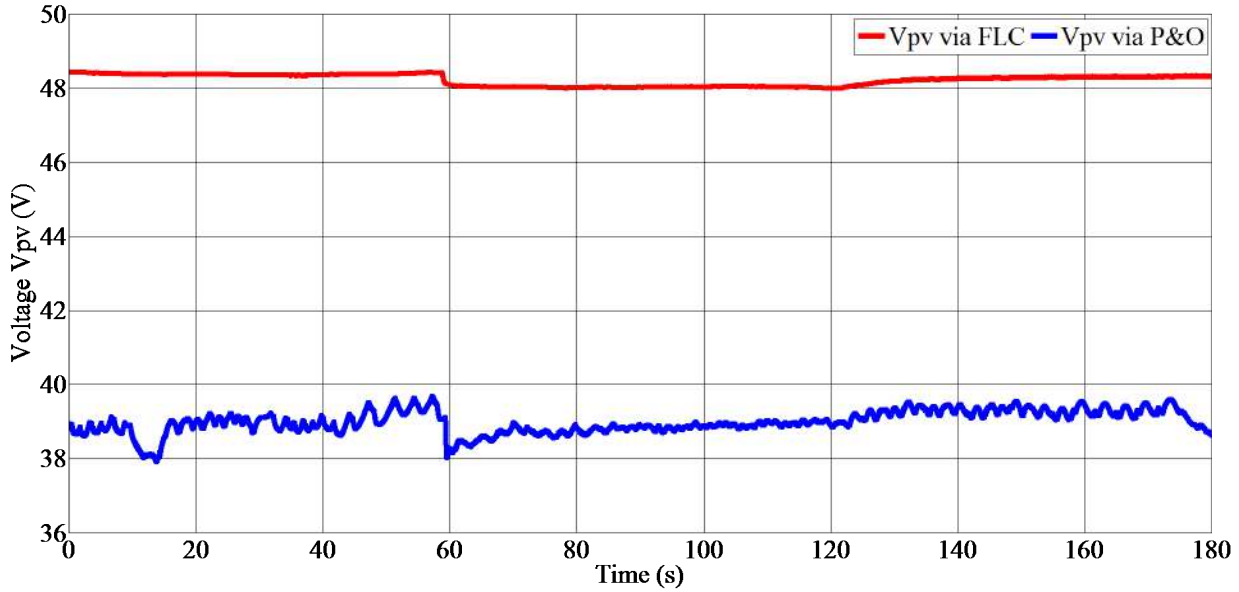


Figure 3.22: Input voltage of boost converter

irradiation and temperature, was rapid and efficient.

- Stability and Accuracy: The algorithm provided stable and accurate tracking of the Maximum Power Point (MPP), minimizing energy loss.
- Adaptability: The FLC algorithm effectively adapted to fluctuations in load and environmental conditions, maintaining optimal performance.
- Hardware Integration: Successful integration with DSpace 1103 hardware showcased the algorithm's robustness and ease of implementation in real-world scenarios. The experimental setup has many limitations that may impact the generalizability and precision

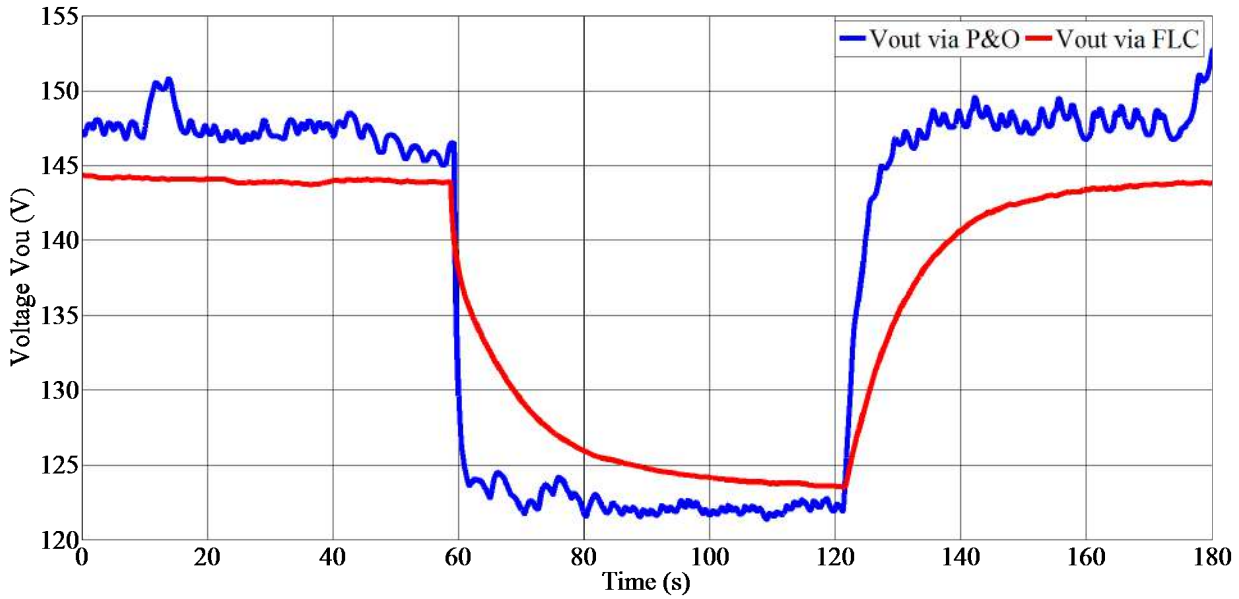


Figure 3.23: Boost Converter Output Voltage

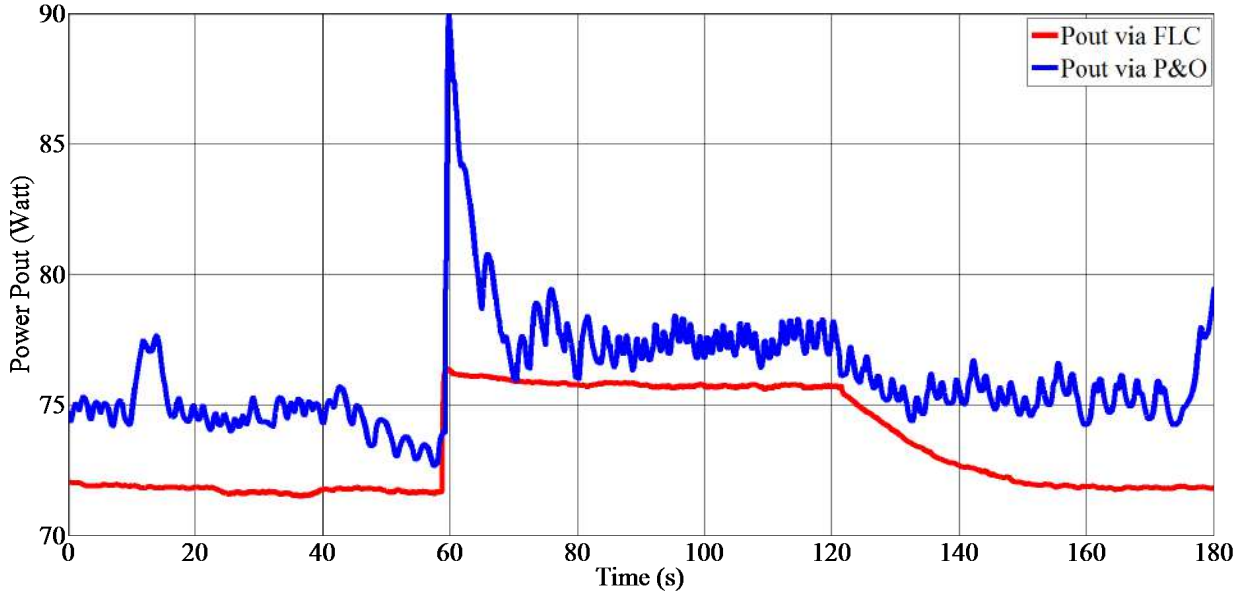


Figure 3.24: Boost Converter Output Power with DC machine load

of the results. Environmental conditions in the controlled setup may not fully replicate real-world variability, such as fluctuating temperatures or grid disturbances. Equipment limitations, involving sensor accuracy and potential calibration errors, could present measurement inaccuracies. The setup's scale and scope are also limiting elements, as small-scale experiments might not charge integration challenges or performance under extreme conditions.

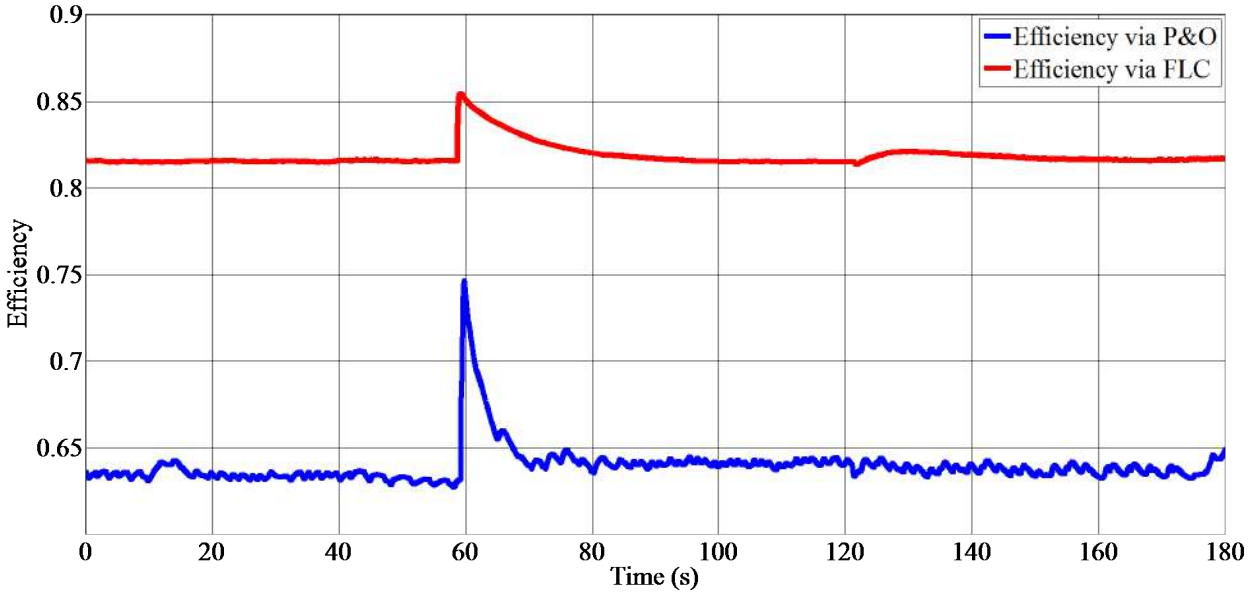


Figure 3.25: Boost Converter efficiency with DC machine load

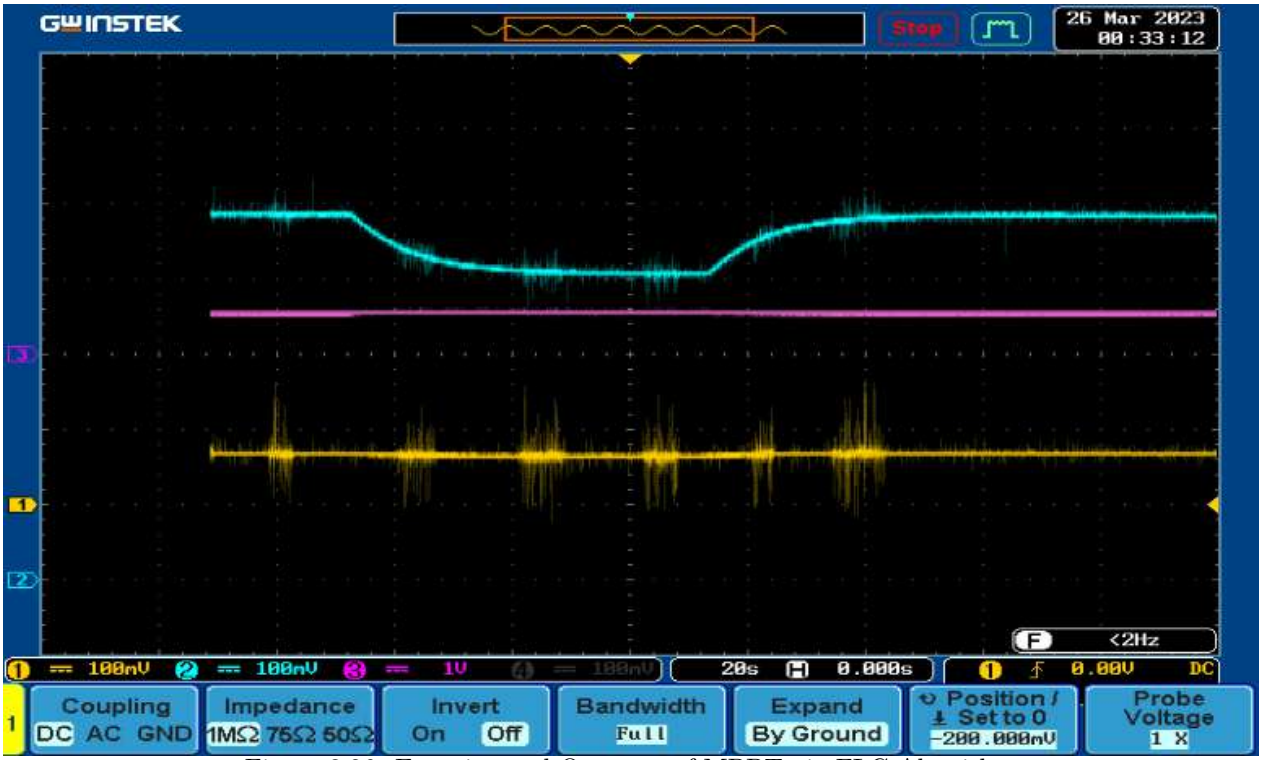


Figure 3.26: Experimental Outcome of MPPT via FLC Algorithm

3.6 Discusion and analysis

Stable Performance Over Time: The proposed FLC-based MPPT strategy proved uniform and stable tracking of t (MPP), even under changing loads and fluctuating environmental conditions like irradiation and temperature variations. This stability reduces energy losses and guarantees optimal power extraction. Rapid Adaptability to Load

Variations: Investigations with varying resistive and DC machine loads indicated that the algorithm quickly adapted to evolutions, keeping smooth voltage and power outcomes with minimal oscillations. The quick response highlights the algorithm's ability to address dynamic functional scenarios effectively. The algorithm was experimented with both fixed and variable resistive loads, as well as with a dynamic DC machine load. With variable Resistive Load: The FLC-based MPPT replied quickly to variations in the load at =60 t=60s and =120 t=120s, confirming minimal disruption in voltage and power outputs. This displays the algorithm's adaptability to dynamic conditions. With DC Machine Load: When the DC machine load was added and removed, the system adapted effectively without showing notable oscillations. This highlights the algorithm's capacity to support performance even with complex and fluctuating loads. Efficiency Maintenance: The outcomes spotlight that the FLC algorithm achieved elevated efficiency, approximately 0.83, regardless of load variations or testing time. This consistency indicates its ability to support performance across prolonged periods. Resistance to Atmospheric Variations: The algorithm's adaptability to sudden atmospheric variations, such as varying irradiation levels, guaranteed stability in power output and decreased susceptibility to oscillations that could otherwise impact system reliability. Reduction in Oscillations: One of the standout segments marked in the experimental results was the notable reduction in oscillations during MPP tracking. This soft performance is due to the fuzzy logic controller's power to use linguistic rules and continuous adjustment of control parameters, which overcome sudden shifts and instability often seen in traditional MPPT methods. The proposed FLC-based MPPT algorithm lowers system costs and energy losses by effectively tracking the maximum power point, hence decreasing power waste under changing conditions. Its durable and streamlined design reduces maintenance needs and allows for the use of low-cost hardware, increasing the total economic viability of solar systems. The proposed FLC-based MPPT system is economically feasible due to its simple construction and efficient performance. The technology lowers operational and installation costs by decreasing energy losses and allowing for the use of low-cost components. Furthermore, its strong performance in a variety of climatic conditions reduces maintenance and downtime, making it more cost-effective for large-scale and grid-connected solar applications.

3.7 Smart Solar Energy Production: Model-5-Pruned Algorithm Based on Optimized Fuzzy Logic Control for Maximum Power Point Tracking Algorithm

In the last decades, renewable energy sources become one of the most attractive issues in both the industrial and literature fields due to the major troubles of fossil fuel energy sources. The monopoly of countries on oil, disputes over the sources of oil production, environmental pollution caused by non-renewable energy, increased annual consumption of energy, need transition process, made solar energy take the major space of energy production among other sustainable energy systems. In addition, it holds enormous promises as a dependable, clean, and efficient supply of our world with power [86] [19]. Due to the solar panel manufacturing costs, intermittency foundation or installation phases, operation lifetime [4], and decommissioning [119], saving the solar panel costs

as much as possible is a significant purpose and competitive field of many companies. Among the choices to upgrade the PV outcomes is the MPPT technique that still the most economical and practical strategy. Many MPPT algorithms were proposed to enhance and increase the efficiency of PV systems, especially, under variations of standard conditions (irradiation and temperature). The DC-DC boost converter is employed to boost the PV panel power. In [120], an overview study on the buck-boost converter is presented with the MPPT technique based on DC microgrids to maximize solar energy production. Solar charge controller adaptive MPPT based on perturbation and observation approach is presented [91].
Constant voltage is another MPPT technique, which achieves quick tracking, simple structure, and flexible implementation [43]. However, it also results in considerable oscillations and creates a notable error value in MPP causing inaccurate tracking. In literature [136], an incremental conductance (INC) approach is carried out to overcome the slow response to sudden atmospheric changes. Despite the (INC) method having good convergence tracking, the fixed step size of increment leads to extra oscillations of the MPP process that in turn, slow down the tracking operation. To avoid the fixed step size increment damages, novel research is proposed adopting the variable step size conception in the INC technique. Although this technique presented remarkable progress in the maximization process of solar energy outcomes and storage systems , however, the requirements of a change of PV panel sloping to adjust the step size and demand a manual tuning according to irradiance level disadvantages this technique. In [136], a novel modification adopts the autonomous scaling factor and slopes the angle variations.
In the last few years, using intelligent algorithms became one of the significant literature topics in PV systems rendering the MPPT process more predictive and adaptive to external atmospheric variations. In [123], a proposition using the FLC algorithm to control the MPPT technique based on the instantaneous current and voltage of the solar panel outcomes, to mitigate the power fluctuations and enhance the MPP technique performance. Another simulation of MPPT founded on FLC is used to develop the efficiency, in order to improve the DC-DC boost converter that can boost the power lack resulting from the sudden reduction of solar irradiance [24]. Despite the FLC achieving a good response in both transient and steady states, FLC has many main defects as taking a long time to computation, implementation difficulties, and dependence on fuzzy sets that cause ambiguous performance, depending on the designer's expertise and understanding of the overall using field, which decreases the system accuracy. The intervention of artificial intelligence was an efficient and strong tool to develop and improve the MPPT strategy, due to its predictive capabilities and its dependence on progressed machine learning algorithms. In [71] context, the ANN algorithm is employed to manage and maximize the PowerPoint process, increase the DC outcomes of solar panels, and adapt to the sudden changes in solar irradiance and temperature.
Despite the ANN realizing notified success in several fields, especially in the control of renewable energy systems, however, the internal structure that still a black box for users and practitioners, A long-time of training, leads to inaccuracy of the control system, and inconsistent performance. In addition, ANN requires big normalized data and more attention in the dataset preparation, where the big size of the dataset leads to slow inaccurate training. Moreover, the implementation complexity and computational analysis difficulties. All that motivates academic researchers looking for another machine

learning able to overcome the aforementioned drawbacks. The primary motivations of this article focus on promoting energy harvesting even in partial shading or non-ideal functional conditions. Adaptable performance to atmospheric variations via continuous learning and updating the control parameters to ensure optimal production despite the variable circumstances are significant motivations. In addition, the traditional MPPT techniques rely completely on mathematical models to estimate the MPP, while the proposed algorithm utilizes the M5P machine learning and pattern recognition to analyze the complex patterns and correlate the dataset in order to raise the tracking accuracy and efficiency. Moreover, the proposed algorithm can be easily scaled and integrated into the PV systems to adjust the large solar installations.

The innovation of this work lies in the novel hybridization between the Fuzzy Logic Controller (FLC) and the M5P machine learning algorithm based on a decision tree model. By combining the human expertise embedded in FLC with the powerful predictive capabilities of the M5P algorithm, the proposed hybrid smart M5P algorithm capitalizes on the strengths of both approaches. This innovative strategy enhances the system's ability to handle sudden external fluctuations, quickly update parameters, and classify and regress data through multiway splitting at each decision tree node. The hybrid approach offers faster response times, improved tracking performance under sudden environmental changes, and efficient energy harvesting, especially in cases of partial shading, as demonstrated by experimental results. The adaptability and predictability of the M5P decision tree significantly elevate the performance beyond traditional MPPT methods.

This chapter contributes the advancing intelligent control systems for PV renewable energy and offers a more efficient alternative to traditional MPPT techniques. In addition, the proposed algorithm includes the optimal performance via the analysis process of large amounts of data to upgrade efficiency and improve the operational performances of the PV system. Furthermore, the proposed model has the potential to enhance reliability and spark the integration of PV systems, which pave the way for ensuring solar energy adoption as a future source more sustainable. Under WEKA and MATLAB software and DSpace 1103, the M5P algorithm has been prepared and achieved in order to accomplish the proposed algorithm.

Artificial intelligence is a novel contribution that aims to increase the adaptive and predictive abilities of MPPT techniques to external turbulences, especially, atmospheric conditions changes. The FLC approach is one of the adaptive methods that uses the linguistic variable to mimic human making [44]. In [69] an optimized model based on FLC to overcome the defects of the traditional MPPT techniques. A concise and well-presented overview of MPPT based on an artificial bee colony (ABC) algorithm used in PV systems to improve the dynamic response and efficiency of the MPPT technique [38]. Operating the PV array at the optimal power even with the external variations of climate situation is a significant improvement, in [49] optimization of the MPPT using the intelligent ant colony algorithm (ACO). A novel amelioration of the MPPT technique based on the grey wolf optimization algorithm (GWO) during the partial shading condition is proposed [96]. In [107] a real-time implementation of the MPPT based on the slide mode controller of a standalone PV system is proposed. A comprehensive evaluation presents the specialized indicators of the classical, FLC, and intelligent MPPT techniques in the PV system are assessed in Table I.

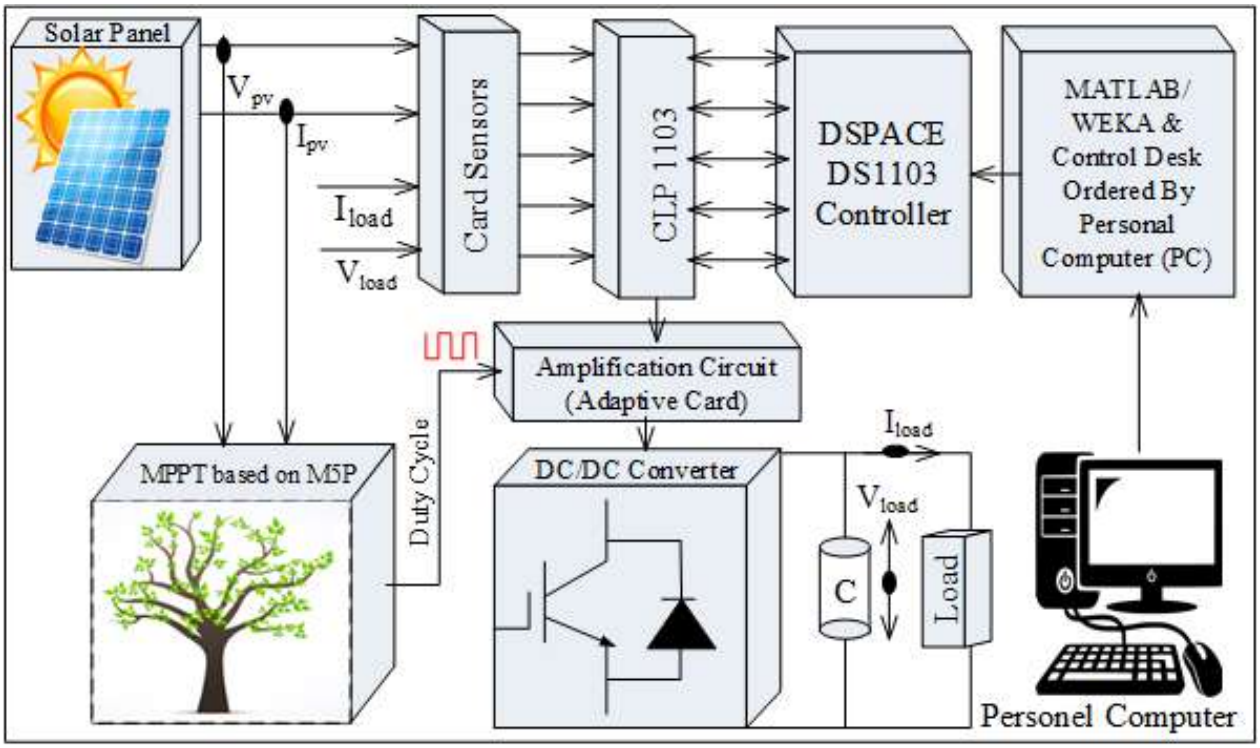


Figure 3.27: General Graphical Abstract

3.7.1 Proposition of M5-Pruned Machine Learning Algorithm

Several Machine Learning Algorithms (ML) are used in different engineering fields, especially, in renewable energy systems, FLC and ANN algorithms are among the famous algorithms that are used to maximize solar panel outcomes. However, the necessity of research on efficient ML, and robust, and investigates a notable development, especially, with rapid development and competitive global growth for renewable energy sources, is considered an urgent and extremely important matter.

3.7.1.1 M5P Decision Tree Conception

Several ML algorithms are used in many fields of engineering, The M5P model is one of the most powerful and efficient ML algorithms, which is based on a combined model between the linear regression and decision tree algorithms. The M5P model consists of three elements: root node, internal node, and leaves. The root node is splitting into other internal nodes, which are interconnected together in sub-nodes to generate the leaves. It can be shown in the Figure.3 (A). To make the predictions, M5P depends on the linear regression model during the training process, and according to the user needs, the datasets (inputs and output) are inserted in the preparation of the training process [34].

3.7.1.2 Decision Tree Difinitio

M5P is used for product classification, clustering, or association rules of individuals and objects. The M5P algorithm uses the (if-then) conditional form that can be carried out

through each path of the tree from root to leaf as illustrated in Figure 13. Thus, the fuzzy logic dataset was a suitable choice proposed M5P algorithm development, because it has the same (if-then) condition in fuzzy rules forms. The decision tree approach arranges the dataset as a tree outline consisting of roots, branches, and leaves. The data classification process to make the predictions is achieved via the following steps: Attribute selection into the root node, choosing the branch, and adding the possible values to the branch, repeating this process in all branches of the tree with only the attribute that connects the branch. To produce the most homogenous leaf, the purity criterion of the leaf is taken into account according to the Gini index as follows:

$$Gini(S) = 1 - \sum_{i}(P_i)^2 \tag{3.11}$$

Where P_i is the purity of data in a subset (S) that belongs to class (i). The attribute that has the highest correlation is selected as the best class. To minimize the prediction of error, the M5P algorithm divides the dataset in each node depending on the chosen attribute. The prediction of error can be estimated for one node (i) by determining the standard deviation concept (S_i). Thus, the standard deviation is defined as follows:

$$\text{SDR} = S_i - \sum_{k=1}^{C} \frac{N_k}{N_i} S_k .... \tag{3.12}$$

Where each node K is occupied by N_k examples, that split to another node (i) in C branches. The mean absolute error (MAE) can be calculated as follows:

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} \left| Y_i - \hat{Y}_i \right| \tag{3.13}$$

Where Y,$\hat{Y}_i$ and n are the actual, predicted value and number of data points, respectively. While the square root of MAE is represented as follows:

$$\text{RMAE} = \sqrt{\left(\frac{\sum_{i=1}^{n} (\hat{Y}_i - Y_i)^2}{n} \right)} \tag{3.14}$$

The coefficient factor (R) based on the linear regression process is calculated as follows:

$$R = \sqrt{\frac{\sum_{i=1}^{n} (\hat{Y}_i - Y_i)^2}{\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2}} \tag{3.15}$$

The linear regression process of the dataset can be expressed as follows:

$$y = \beta_0 + \beta_1 a_1 + \cdots + \beta_p a_p \tag{3.16}$$

Where y, α, and β are the predicted target, attribute values, and regression weights, respectively.

3.7.1.3 Regularization of the Model

Regularization includes the construction of an average model to move from one leaf to another leaf of the tree. This process leads to discontinuities in predictions. Throughout the M5 framework, regularization starts by building a linear model for all the tree nodes as shown in Figure 3 (B). In the average model, the average weights are taken as predicted values as predictive examples in each model received at each node.

3.7.1.4 Attribute

Attributes are the basis for splitting the data and creating a hierarchical structure that permits effective decision-making and classification.

3.7.1.5 Missing Value

The versatile ability of the M5-Pruned algorithm can deal with the missing values via many technical methods involving: replacing the missing value with a default value as a mean or median value using the imputation technique to another value in the dataset. Ignoring the missing value is another method based on ignoring the instance of the missing value, but this method can lead to less accuracy.

3.7.1.6 Pruning

Pruning in the decision tree algorithm is a technique used to analyze the dataset and improve the performance of making a suitable decision. There are two types of pruning: pre-pruning and post-pruning. In pre-pruning, the decision tree building is stopped when the pruning reaches a certain depth sufficient to make the final decision according to certain criteria. In post-pruning, the decision tree algorithm is trained until reaches its full depth, the repruning back in some nodes to remove the nodes that capture the noise to simplify the tree without lack of accuracy.

3.7.2 Dataset Extraction and Training Process via FLC Algorithm

The dataset extraction process is achieved by taking the inputs and outputs of the FLC algorithm and memorizing the dataset in Matlab workspace software. Then, the dataset is imported via Weka software to train and generate the M5P algorithm as shown in Figures 4, and 2.

3.7.3 Perturbation and Observation Technique based on the proposed M5P algorithm

One of the major defects of the *P&O* method is the significant oscillations that lose solar panel power and decrease the accuracy of the MPPT strategy. Prediction and fast response are important issues, especially, in solar system generation due to the instantaneous changes in irradiance and temperature [43]. Hence, decision tree choice is an appropriate solution that investigates great experimental results and good adaptation to climate turbulences. Figure. 11 shows the *P&O* method based on the proposed M5P

decision tree algorithm. Under WEKA software, the M5P decision tree model has been extracted as shown in Figures. 13 and 14.

Table 3.2: Hardware and software specifications of the system

Tool	Specification	Tool	Specification
1	DSPACE DS1103: hardware platform developed for fast control supplies real-time processing abilities for automotive and industrial control techniques.	9	Three FLUKE 177 TRUE RMS Multimeters
2	Current and voltage card sensors LEM (LA25-P, LV25-P)	10	Power supply
3	Incandescent lightbulb	11	Inductors 10mH
4	DC multi-circuit machine SE2682-3D	12	Solar Panel Wire
5	Control Desk: experiment with software for seamless ECU development	13	Real Solar Panel (200 Watt)
6	CP1103 / CLP1103 Breakout Box connection panel	14	Digital Oscilloscope GDS3054
7	Switchable Resistive and capacitive Loads	15	DC generator
8	Adaptive Card between Semikron (Converter Device) & DSPACE 1103	16	Semikron DC/DC Converter

Table 3.3: Specifications parameters of DC machine load

Parameter	Value	Unit
Nominal Voltage	200	V
Nominal Current	1.3	A
Exciter Voltage	220	V
Exciter Current	100	mA
Nominal Speed	2030	rpm
Nominal Power	0.2	kW

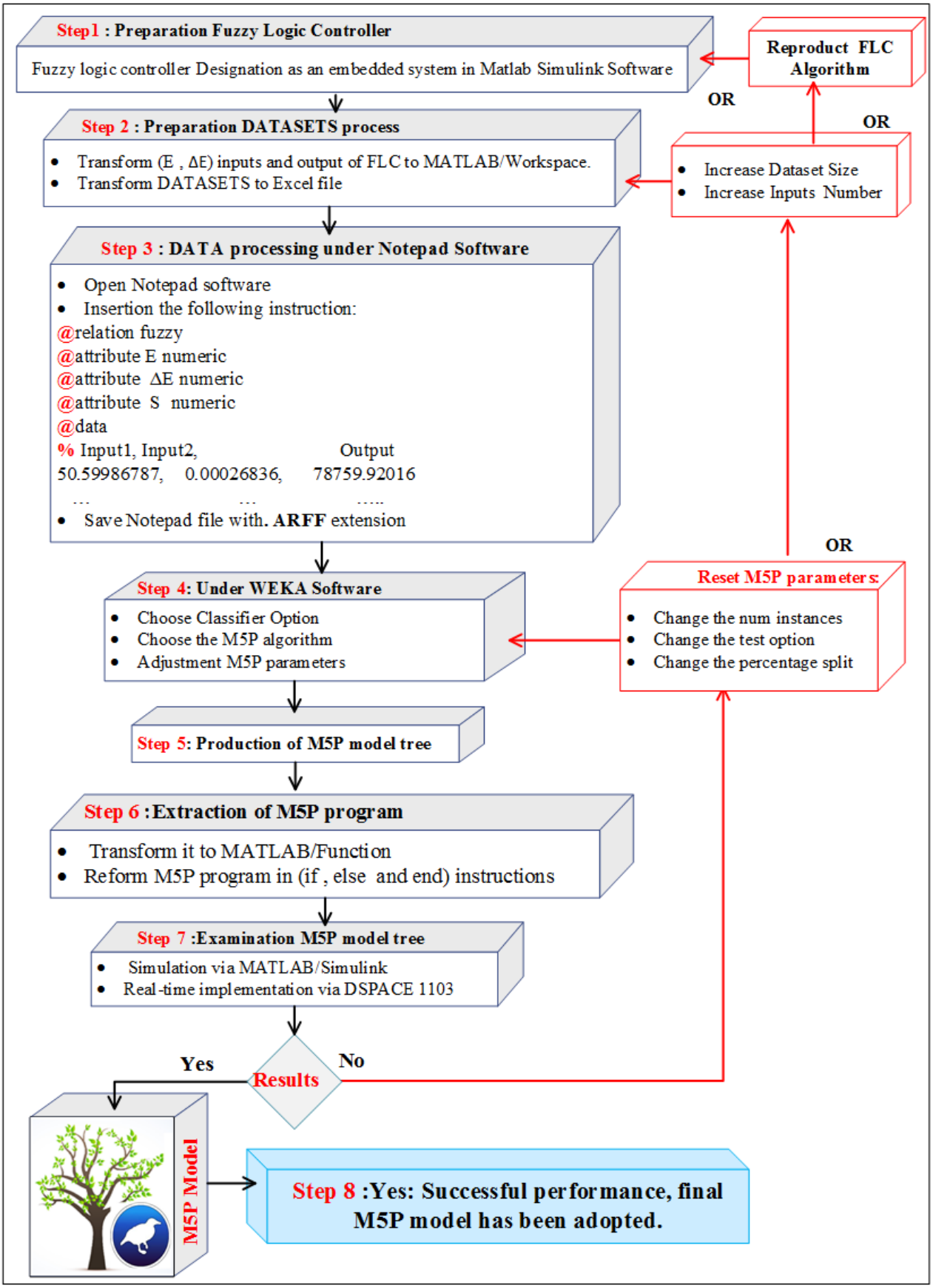


Figure 3.28: Flowchart of Research Methodology

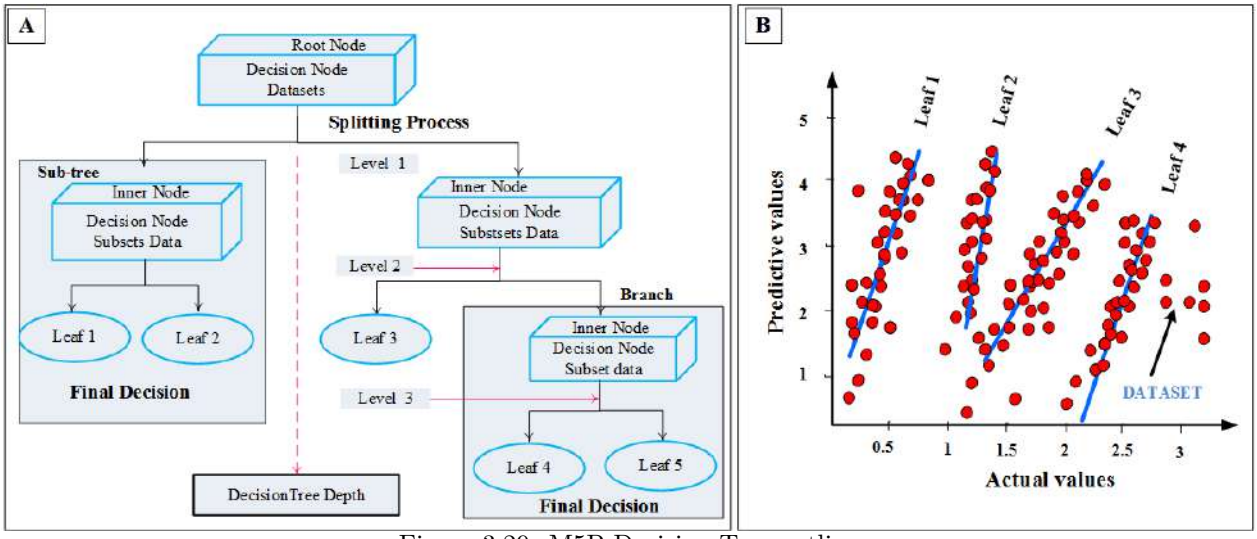


Figure 3.29: M5P Decision Tree outline

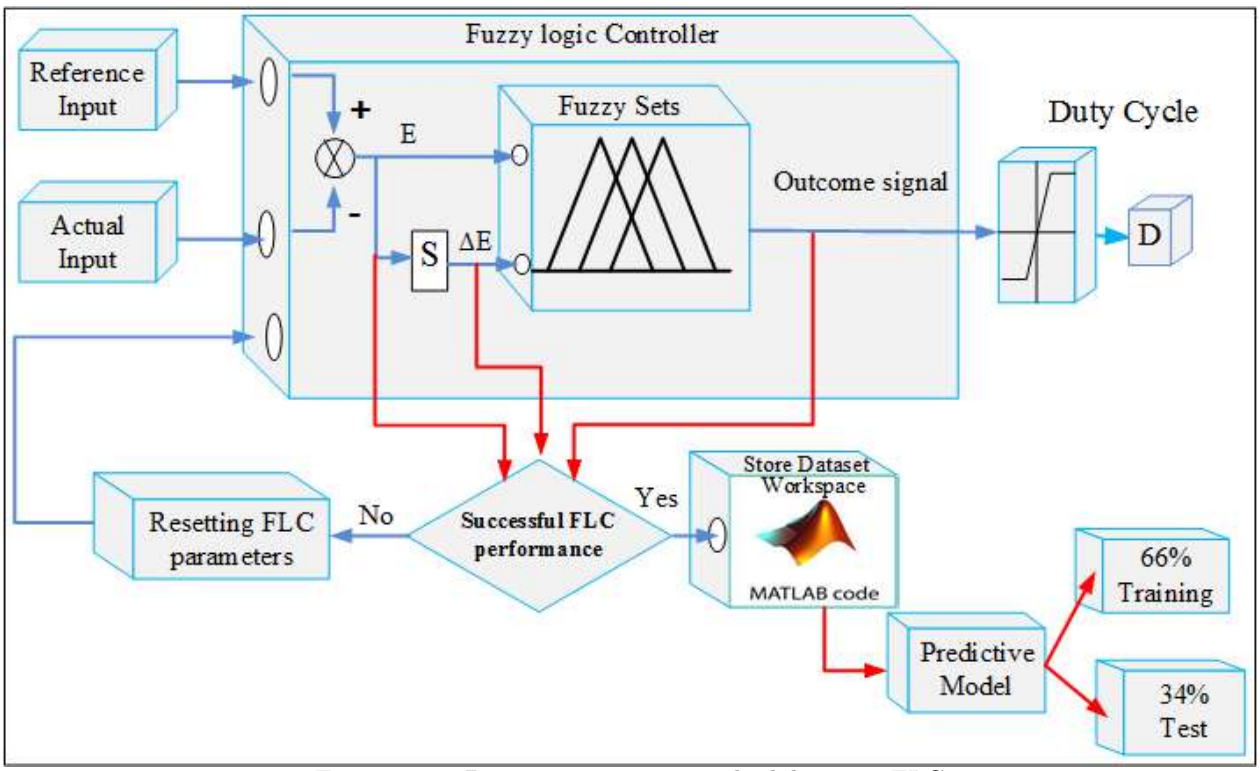


Figure 3.30: Dataset extraction methodology via FLC

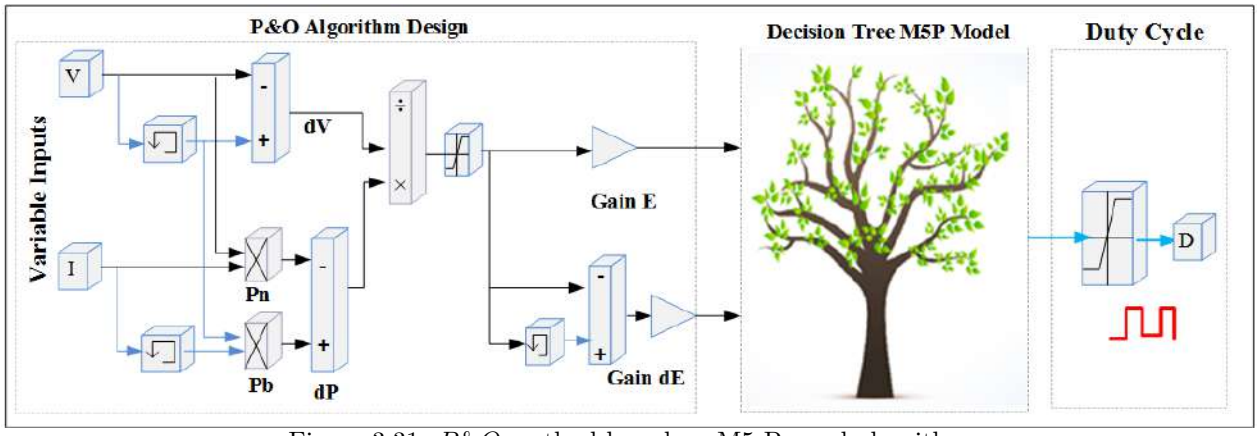


Figure 3.31: *P&O* method based on M5-Pruned algorithm

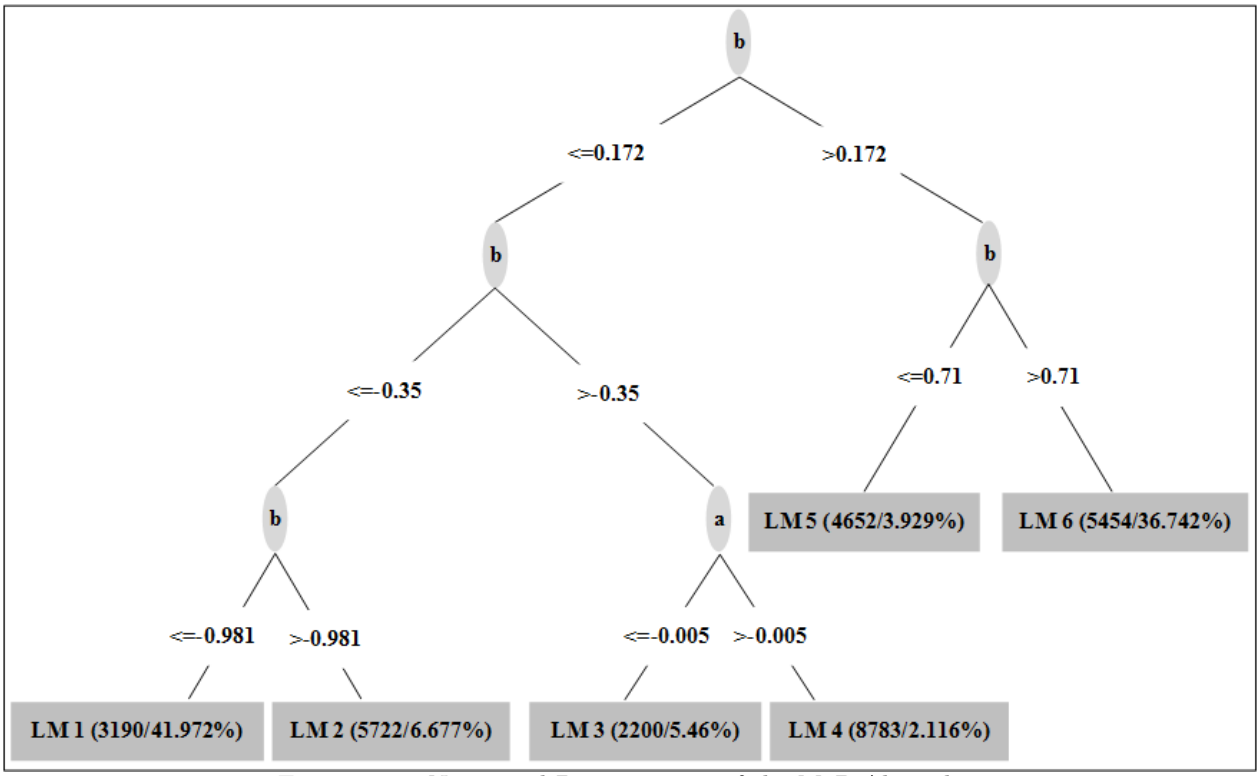


Figure 3.32: Numerical Decision Tree of the M5P Algorithm

=== Run information ===

Scheme: weka.classifiers.trees.M5P

Relation: fuzzy → Name of dataset

Instances: 30001 → Dataset Size

Attributes: 3

a, b → 2 inputs (E & dE)

c → 1 output (Duty cycle)

Test mode: evaluate on training data

=== Classifier model (full training set) ===

M5 pruned model tree:

(using smoothed linear models)

LM1=1.0512 * a - 0 * b - 1.3423;

LM2=1.0801 * a + 1.0046 * b - 0.1371;

LM3=1.0365 * a + 1.4647 * b - 0.0206;

LM4=1.0342 * a + 1.3751 * b + 0.0041;

LM5=1.0322 * a + 1.111 * b + 0.0729;

LM6=0.8908 * a - 0 * b + 1.1719;

b <= 0.172 :

| b <= -0.35 :

| | b <= -0.981 : LM1 (3190/41.972%)

| | b > -0.981 : LM2 (5722/6.677%)

| b > -0.35 :

| | a <= -0.005 : LM3 (2200/5.46%)

| | a > -0.005 : LM4 (8783/2.116%)

b > 0.172 :

| b <= 0.71 : LM5 (4652/3.929%)

| b > 0.71 : LM6 (5454/36.742%)

Number of Rules : 6

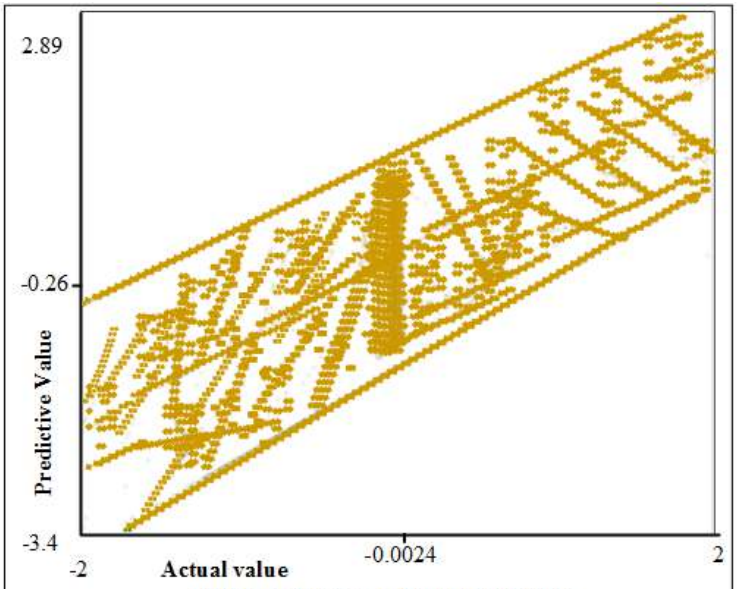
Time taken to build model: 0.5 seconds

=== Evaluation on training set ===

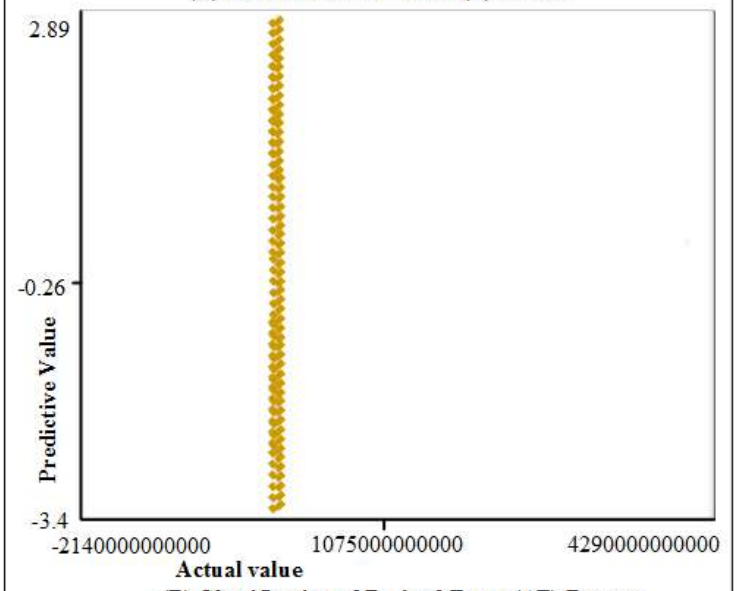
Time taken to test model on training data: 0.02 s

=== Summary ===

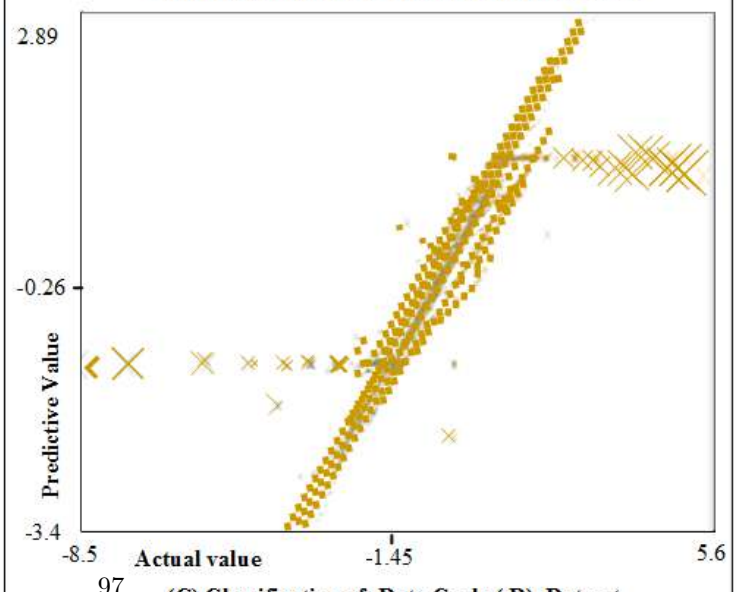
Correlation coefficient	0.9774
Mean absolute error	0.0715
Root mean squared error	0.1795
Relative absolute error	10.9369 %
Root relative squared error	21.1466 %
Total Number of Instances	30001



(A) Classification of Error (E) Dataset



(B) Classification of Derived Error (ΔE) Dataset



(C) Classification of Duty Cycle (D) Dataset

Figure 3.33: Outcomes of the M5P model via WEKA Software

3.8 Experimental Results

To achieve the comparative experimental tests and validation processes of the conventional MPPT-FLC method and proposed smart MPPT-M5P algorithm, the system requires specific devices and equipment. Table III provides the hardware and software specifications of the system. In this section, the experimental validation tests are achieved in fixed and variable resistive load conditions. Under DSPACE 1103 hardware, MATLAB/Simulink, WEKA, and Control Desk software, the experimental validation tests are carried out. Figs. 3.27 and 3.14 show the configuration scheme of the experimental setup platform. The specifications of the experimental parameters of the solar panel, boost converter, and DC machine are listed in Tables 3.1.

MATLAB/Simulink (Software)

- **Version**: MATLAB R2012a
- **Purpose**: Used extensively for end-to-end system simulation and algorithm development. Specifically, it was employed to design and validate the MPPT algorithm, simulate solar PV behavior, and model power conversion stages.
- **Toolboxes Used**: Simulink, SimPowerSystems, Fuzzy Logic Toolbox, Simulink Control Design, Data Import/Export Tools.
- **Role**: Enabled modular, scalable modeling of the hybrid MPPT system. Supported fault injection, parameter sweeps, load variation, and comparative benchmarking. Provided realistic I-V and P-V curves for ML training and testing.

WEKA (Software)

- **Version**: WEKA 3.8
- **Purpose**: Data mining and machine learning platform for training and evaluating the M5-pruned decision tree using MATLAB simulation datasets.
- **Algorithms Applied**: M5P Regression Trees, 10-fold Cross-Validation, Pruning Techniques.
- **Role**: Extracted lightweight, interpretable rules for MPPT logic. Allowed data-driven model generation and export to Simulink for deployment in real-time control.

DSpace DS1103 (Hardware)

- **Purpose**: Real-time controller for hardware-in-the-loop validation of the MPPT algorithm, interfacing with PV emulator and DC-DC converter.
- **Specifications**: PowerPC 750GX @ 1GHz, 20 analog inputs, PWM support, real-time I/O, CP1103 breakout box.
- **Role**: Executed the control algorithm in real time, generated PWM signals, interfaced with LEM sensors for current/voltage sensing. Enabled closed-loop hardware validation and safety monitoring.

ControlDesk (Software)

- **Version**: ControlDesk 3.x
- **Purpose**: Real-time interface for visualization, data logging, and parameter tuning during experimental implementation.
- **Features**: Signal monitoring, transient logging, dashboard creation, live tuning of fuzzy sets and decision thresholds.
- **Role**: Accelerated testing cycles, improved debugging, enabled efficient real-time interaction with the DSpace DS1103 hardware environment.

3.8.1 Experimental Results with Fixed Resistive Load

In this experiment, comparative results between the FLC and M5P algorithms have been validated under fixed resistive load conditions for three minutes. This experiment aims to isolate the system and observe the behaviour in the steady state condition, which ensures the reliability of results.

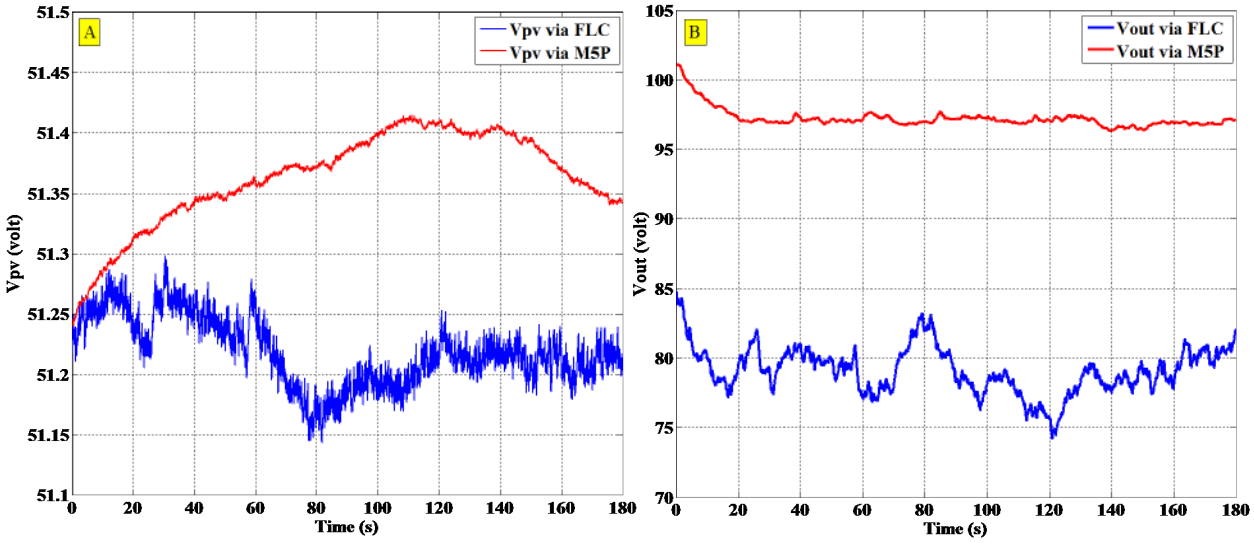


Figure 3.34: Income and Outcome voltages of Boost Converter

Figure. 3.34 (A) shows the output voltages of solar panels, it is clear that the input voltage of the $P\&O$ strategy based on the proposed M5P algorithm is more saturated and free of disturbances, which proves its ability to decrease the oscillations, unlike the $P\&O$ based on FLC as shown in the same Figure. While Figure. 18 (B) proves the M5P capacity to increase the outcome voltage of the boost converter, which reaches 97 volts compared with the FLC algorithm, which fulfils 77 volts.
Figures 3.35 (A) and (B) illustrate the solar panel currents I_{PV} (A) and I_{out} (A) of boost converter, respectively for the FLC technique and proposed M5P algorithm, it is clear that the M5P algorithm presented stable behaviour, was able to compensate for the turbulences, and adapted to the atmospheric changes.
Figures. 3.36 (A) and (B) present the outcome power of the PV panel V_{PV} (W) and

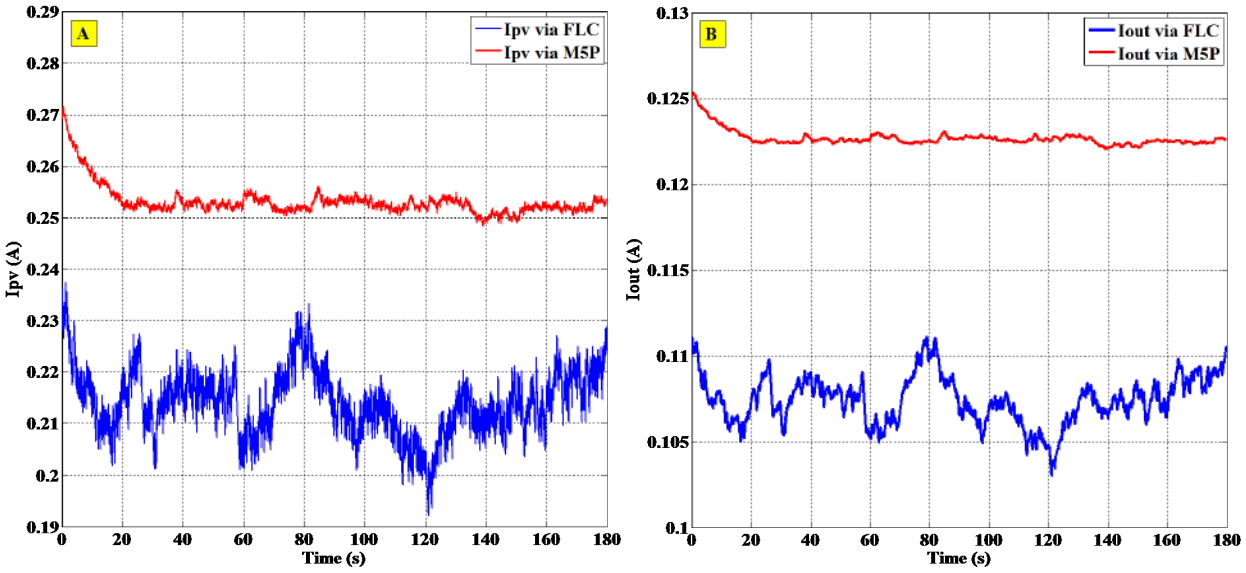


Figure 3.35: Income and Output Currents of Boost Converter

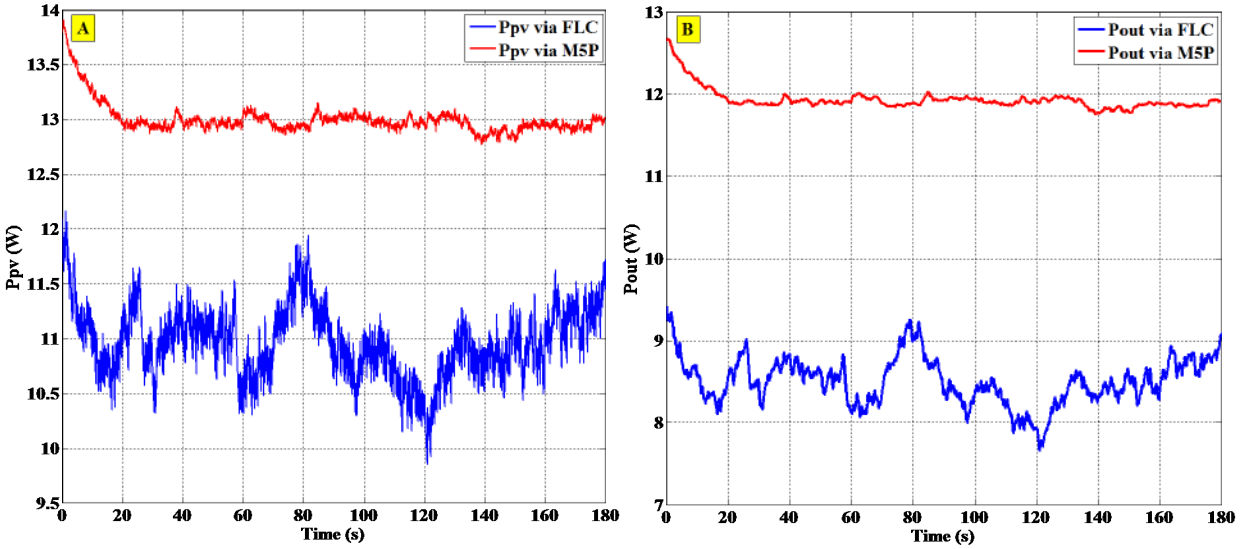


Figure 3.36: Income and Outcome Powers of Boost Converter

output power of the boost converter P_{out} (W).It is noticeable that the M5P algorithm achieved better power performance compared with the FLC algorithm. We would like to point out that although the maximum power of the used solar panel reached 200 W as shown in Table 3.1, the loads used in this experiment consumed just 13 W as shown in Table 3.1.

In order to justify that the proposed M5P algorithm is more efficient than the FLC algorithm, Figure. 3.37 illustrates the comparative efficiency that can be given in the following form:

$$\eta = \frac{P_{out}}{P_{PV}}$$

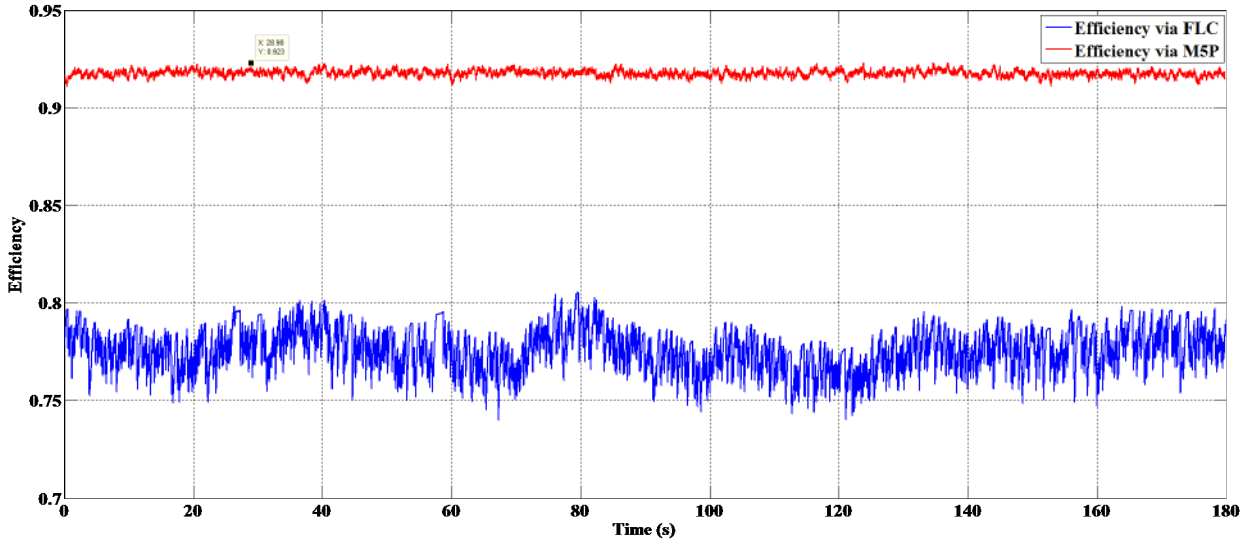


Figure 3.37: The efficiency of the Boost Converter

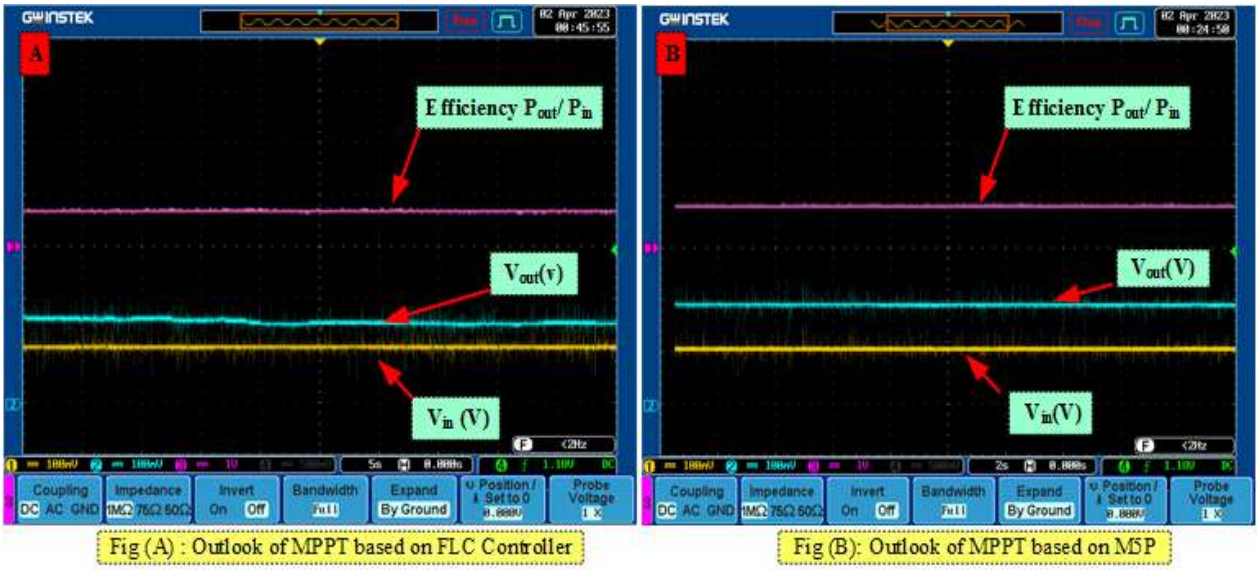


Figure 3.38: Comparative Results between MPPT based on FLC and M5P

where the $M5P_{eff} = 0.92$ while the $FLC_{eff} = 0.74$. Using Oscilloscope device, Figures. 3.37(A) and (B) describe the performances of both algorithms FLC and proposed M5P, respectively. Figure. 3.37 (A) presents the V_{in} (v), V_{out} (v), and efficiency of the FLC algorithm, while Figure. 3.34 (B) illustrates the V_{in}(v), V_{out} (v) and efficiency of the proposed M5P algorithm. It is clear that M5P was able to overcome the oscillations and achieved stable performance and accurate results compared to the FLC algorithm.

3.8.2 Experimental Results with Variable Resistive Load

To test the robustness and effectiveness of the proposed M5P algorithm in comparison with the FLC algorithm and investigate the fast response with the sudden variations, an extra resistive load is injected at the second minute and removed at the third minute. This test aims to explore and observe the relationship between the manipulated resistive

variable and the outcomes in the runtime 60s and 120s.

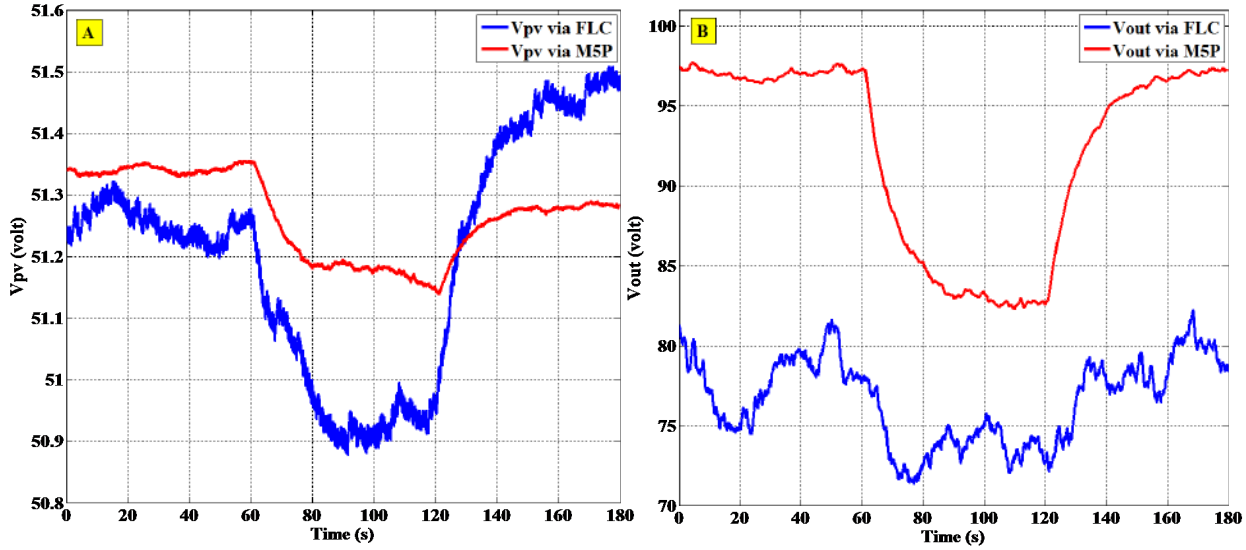


Figure 3.39: Income and Outcome voltages of solar panel

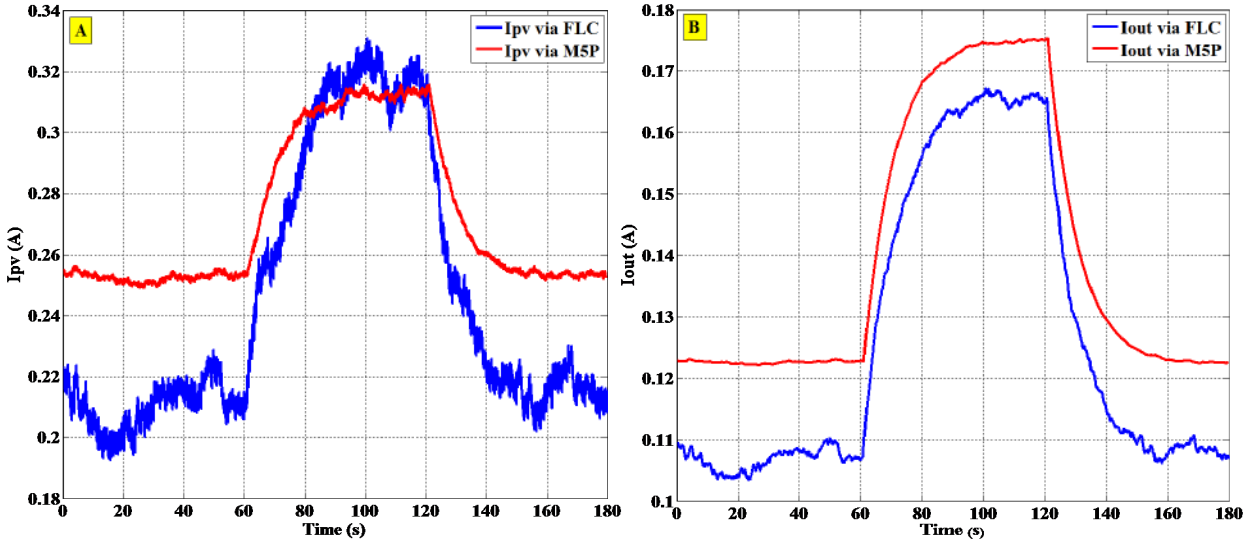


Figure 3.40: Income and Outcome Current of Boost Converter

Figures. 3.39 (A) and (B) illustrate the output voltages of the PV panel V_{PV} (volt) and DC/DC converter V_{out} (volt), respectively, for both proposed M5P and FLC algorithms. It can be observed that the V_{PV} (volt) of the proposed M5P algorithm is more filtered, free of oscillations, and achieves a fast runtime response during (60 s and 120 s), compared with the FLC algorithm, where it can be seen that the distorted, unstable outcome of the FLC algorithm. Moreover, it is obvious that the proposed M5P algorithm increased the DC/DC V_{out} (volt) bigger than the FLC algorithm, as shown in Figure 3.39 (B).

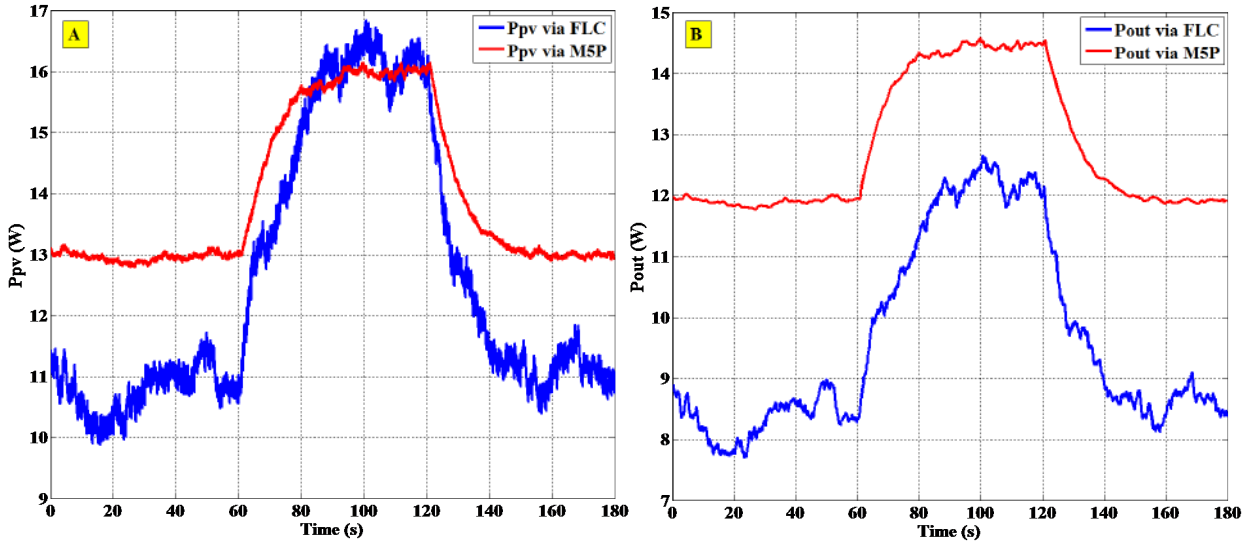


Figure 3.41: Input and Output Power of Boost Converter r

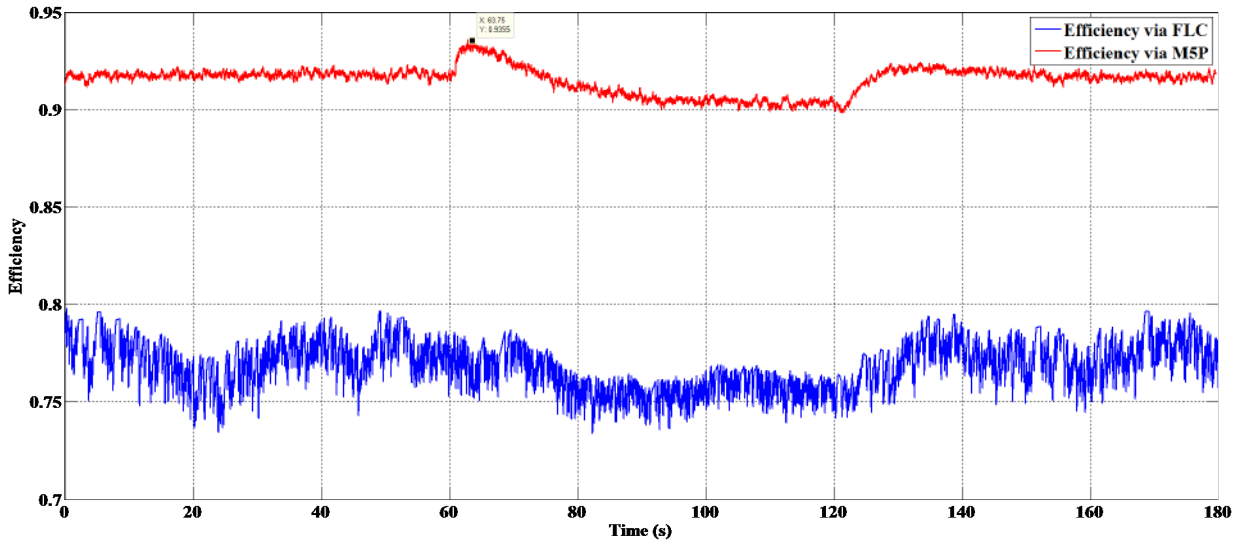


Figure 3.42: The efficiency of the Boost Converter

Figures. 3.40 (A) and (B) show the output current of the solar panel I_{PV} (A) DC/DC converter I_{out} (A), respectively. It can be noticed that the proposed M5P algorithm was stable, free of harmful oscillations through the steady state, and quickly responsive compared with the FLC algorithm in the transient states.

Figures. 3.41 (A) and (B) show the output power of the PV panel and output power of the DC/DC converter, respectively for both proposed M5P and FLC models. The proposed M5P algorithm has a uniform waveform compared with the FLC controller. The M5P algorithm proves its adaptation ability to sudden fluctuation and external

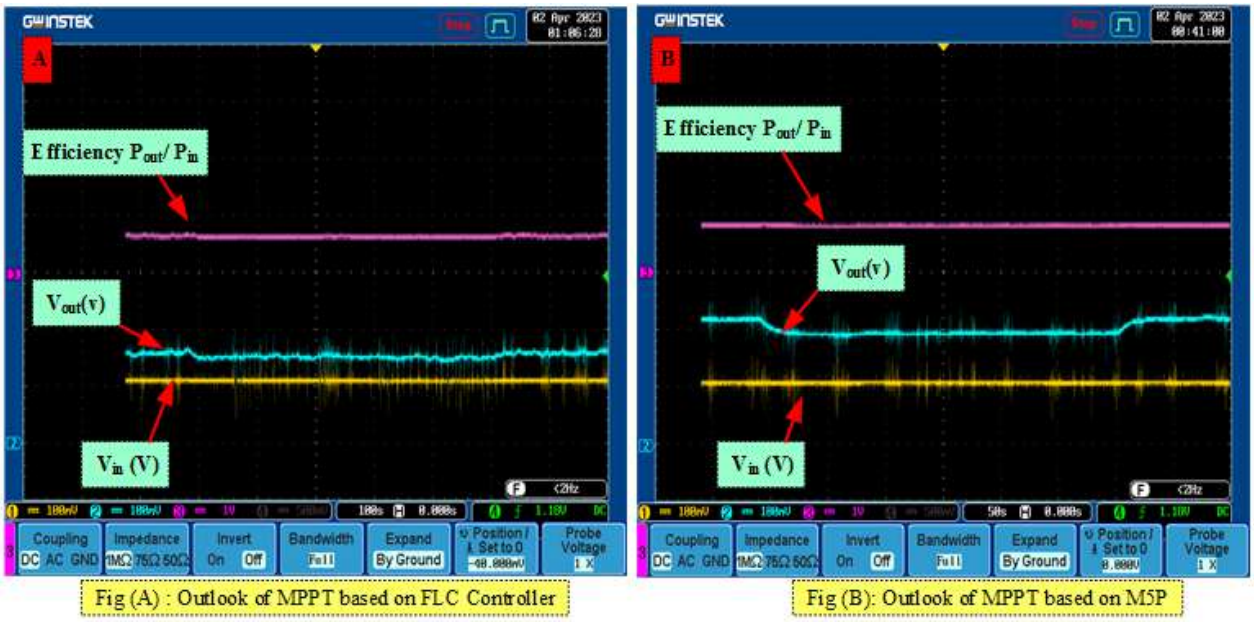


Figure 3.43: Comparative Results between MPPT based on FLC and M5P

changes. On the other hand, it can be noticed that M5P overcame and decreased the broadband oscillations of the FLC and achieved a stable performance through the steady state and fast response at the transient state in the runtime (60s and 120s). I would like to point out that although the maximum output power of the solar panel reaches 200 (watts) Table II, the embedded load consumed just about 16% of the solar panel power returned to nature of the load and its parameters as shown in Table IV and Figure 3.5. Figure. 3.42 offered efficient performance that can be expressed by:

$$\eta = \frac{P_{out}}{P_{PV}}$$

It can distinguish clearly the performance of the two comparative proposed M5P and FLC algorithms, where it can be seen that the η_{M5P}=0.92, while the η_{FlC}=0.75, and it can be noted that the proposed M5P algorithm decreases the broadband oscillations of the FLC and keeps a stable and fast response adaptive behaviour compared with the FLC technique. It also demonstrated the effectiveness and robustness of the proposed algorithm. Via using the Oscilloscope device, a collective monitored figure gathers both compared algorithm M5P and FLC performances in Figure 3.43 (A) and (B), respectively. It is clear the superior and uniform behaviour of the M5P technique compared with the FLC technique. In addition, the fast and clear response of the proposed M5P algorithm. In tabular and statistical presentation of the obtained results is shown in Figure. 3.44 and Table V, respectively.

Table 3.4: Comparative numerical experimental results

Strategy	**V_{pv} (V)**	**V_{out} (V)**	I_{pv} (A)	**I_{out} (A)**	**P_{pv} (W)**	**P_{out} (W)**	**Efficiency**
MPPT-FLC	51.26	77	0.210	0.107	11	8.2	0.74
$\pm\Delta e$ of MPPT-FLC	0.10	15	0.020	0.005	0.002	0.075	0.05
MPPT-M5P	51.35	97	0.253	0.123	13	12.0	0.92
$\pm\Delta e$ of MPPT-M5P	0.01	0.5	0.010	0.0004	0.0001	0.025	0.0045

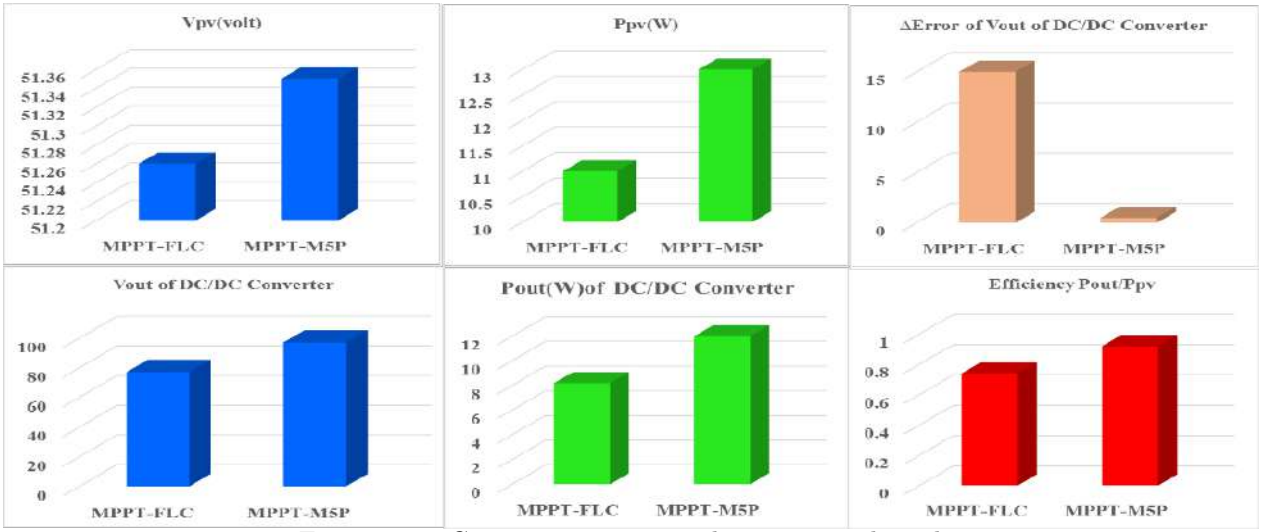


Figure 3.44: Comparative statistical experimental results

In brief, this subsection presented an innovative hybrid intelligent approach that integrates the M5-pruned (M5P) algorithm with an FLC to improve MPPT via the ($P\&O$) method. The erratic variations in irradiance and temperature directly affect solar power generation, resulting in heightened oscillations in MPPT efficiency and, thus, squandered solar energy. The M5P-FLC hybrid algorithm successfully addresses these problems by providing predictive, rapid, and efficient tracking through a streamlined structure and improved accuracy. The proposed algorithm's primary benefit is in its capacity to efficiently handle extensive datasets within a brief training period, while offering a viewable numerical analysis via a programmed decision tree, setting it apart from traditional machine learning methods. The amalgamation of M5P and FLC harnesses the advantages of both algorithms, yielding an intelligent MPPT method with enhanced adaptability and accuracy. The efficacy of the suggested method was confirmed by comprehensive experimental evaluations utilizing MATLAB/Simulink, WEKA software, and DSpace 1103 hardware. The findings exhibited the algorithm's superior efficiency, rapid convergence, and accurate tracking skills. Nonetheless, a constraint of the M5P method is its confinement to (MISO) systems, necessitating a singular output during training. To address this limitation, different ML methodologies, such (SVM) and Gaussian Processes, may be investigated. Nonetheless, considering that MPPT is fundamentally a MISO system, the M5P algorithm was deemed the most appropriate method for this investigation. Subsequent research will concentrate on advancing this study in two principal avenues: enhancing (DTC) for (DFIG) through the M5P decision tree algorithm to optimize wind energy applications, and incorporating an embedded M5P algorithm within hybrid renewable energy systems, specifically in isolated wind-solar microgrids, to augment energy availability and reliability for rural electrification. The encouraging outcomes of this study create new opportunities for enhancing intelligent MPPT methodologies and improving renewable energy conversion systems.

3.9 Conclusion

This work presented an innovative hybrid intelligent approach that integrates the M5-pruned (M5P) algorithm with a (FLC) to improve (MPPT) via the (P&O) method. The erratic variations in irradiance and temperature directly affect solar power generation, resulting in heightened oscillations in MPPT efficiency and, thus, squandered solar energy. The M5P-FLC hybrid algorithm successfully addresses these problems by providing predictive, rapid, and efficient tracking through a streamlined structure and improved accuracy. The proposed algorithm's primary benefit is in its capacity to efficiently handle extensive datasets within a brief training period, while offering a viewable numerical analysis via a programmed decision tree, setting it apart from traditional machine learning methods. The amalgamation of M5P and FLC harnesses the advantages of both algorithms, yielding an intelligent MPPT method with enhanced adaptability and accuracy. The efficacy of the suggested method was confirmed by comprehensive experimental evaluations utilizing MATLAB/Simulink, WEKA software, and DSpace 1103 hardware. The findings exhibited the algorithm's superior efficiency, rapid convergence, and accurate tracking skills. Nonetheless, a constraint of the M5P method is its confinement to (MISO) systems, necessitating a singular output during training. To address this limitation, different ML methodologies, such (SVM) and Gaussian Processes, may be investigated. Nonetheless, considering that MPPT is fundamentally a MISO system, the M5P algorithm was deemed the most appropriate method for this investigation. Subsequent research will concentrate on advancing this study in two principal avenues: enhancing (DTC) for Doubly Fed Induction Generators (DFIG) through the M5P decision tree algorithm to optimize wind energy applications, and incorporating an embedded M5P algorithm within hybrid renewable energy systems, specifically in isolated wind-solar microgrids, to augment energy availability and reliability for rural electrification. The encouraging outcomes of this study create new opportunities for enhancing intelligent MPPT methodologies and improving renewable energy conversion systems.

Chapter 4

Advancing Wind Energy Conversion: Smart Maximum Power Point Based on M5-Pruned Algorithm for Enhanced Wind Energy Production

4.1 Introduction

Global energy crises [29], monopoly of oil and gas [36], especially with the Ukrainian-Russian war [51], pollution troubles [3], global warming [83], and increasing power consumption [8] of the world have made wind energy one of the significant renewable energy sources [99] in the last decades and put wind energy on the top of the new scientific research list. Wind energy is considered a powerful renewable energy source that developed dramatically in recent years because of technological progress and became the most effective type of renewable energy [12, 148]. The wind power maximization process is a significant topic that can be achieved via many techniques and developed methods such as expanding wind farm capacities [82], turbine technology advancement [88], size and height turbine improvement, and blade design research [23]. Despite these methods being effective, they are still the most costly and described by many defects. Research and development is a significant topic that can save a lot of effort and costs and lead to considerable progress in wind turbine materials, technologies and manufacturing processes, which in turn reduce the cost as little as possible and increase the efficiency and reliability of wind power systems [155]. Increasing the wind power generation via the MPPT technique is the most applicable and efficient method [104]. Hence, the achievement of a notable advancement in the MPPT algorithm is considered the main goal of this study. MPPT based on the P&O conception [97] has been used to eradicate conventional MPPT defects. The P&O method improved the wind energy harvesting from the wind turbine through accurate tracking and efficient optimization via adjusting the operating conditions of the wind turbine [142]. Simplicity, low cost, wide applicability and computability with the storage are the significant advantages of the P&O

method, however, there are also some limitations and defects as significant oscillations around the MPP that cause fluctuations in the wind power, reduced system efficiency and cause mechanical stress on the turbine component. The incremental conductance (INC) method [153] is another technique of the MPPT, which analyses the derivative power curve concerning the generator speed or blade pitch angle. The comparison process of derivative to zero is used to determine the direction in which the output of power increases and adjust the operating point accordingly. Although the INC method has achieved tangible fulfilment in the MPPT operation as fast response, accurate tracking, wide applicability and simplicity of implementation. However, after applying the INC technique in some industrial wind power systems, has been found that the oscillations around the MPP, sensitivity to noise and measurement error, complexity in turbulent wind conditions, as well as the limited adaptability in certain wind variations of wind-specific turbine design are major drawbacks that decrease the MPPT efficiency. An MPPT technique based on a simple, real-time, optimized and applicable algorithm is the Hill Climbing Search (HCS) [141]. HCS technique uses the comparison process between the adjusted speed of the wind generator or blade pitch angle and the output power, where, if the power is increased, the HCS algorithm continues in the same direction, otherwise, this method adjusts the operating point in the opposite direction repeatedly until reaching the maximum power point. Local optima, sensitivity to the initial conditions [126], slow convergence and sensitivity to noise and measurement errors are the significant issues of this method. Other approaches have been proposed for MPPT in wind power systems, such as the progressive multi-sector P&O method, which improves the efficiency of the wind power conversion process [41]. The slide mode control SMC technique has also been used in wind power systems, highlighting its application in controlling systems [130]. Additionally, multivariable optimal control founded on an incremental state model has been employed to handle the wind turbine dynamics [151]. However, these classical methods show considerable limitations. The progressive multi-sector P&O method, though enhanced, often suffers from slow convergence and ripples near the maximum power point, especially in rapidly varying wind conditions. SMC can present chattering effects, reducing overall design performance and efficiency. The multivariable optimal control can meet challenges when used in more complex, dynamic wind environments due to advanced computational requirements and tuning difficulties. Research based on artificial intelligence technologies in wind power systems has witnessed numerous developments in maximum power point tracking (MPPT) strategies to improve the performance and efficiency of wind energy conversion. Many smart control techniques have been proposed, each leveraging various techniques and algorithms to optimize the output. For instance, a study using integral sliding mode control for Doubly Fed Induction Generator (DFIG) wind energy systems incorporates ANN for MPPT, proving enhanced performance under real wind conditions [41]. Social Spider Monkey-Particle Swarm Optimization (SSM-PSO) is another smart approach to improve the efficient MPPT method [126]. The Ant Colony Algorithm has been used to MPPT in wind turbines, offering significant advances in tracking accuracy [98]. Moreover, wind speed forecasting employing advanced algorithms such as the Multi-Objective Grey Wolf Optimization has been applied to improve the conversion of wind power systems [7]. While the aforementioned studies provide developed MPPT methods, they have many drawbacks. Ant Colony and Grey Wolf optimization introduces complex structure and

computational issues and slow response times, which can restrict real-time performance. Additionally, the use of ANN and FLC may be sensitive to parameter tuning, which reduces the robustness of dynamic wind conditions. Wind speed forecasting techniques often struggle with accuracy in rapidly varying wind conditions, which can decrease the overall efficiency of the MPPT strategy. In comparison to other state-of-the-art techniques, the proposed algorithm presents a comparison to the intelligent Runge Kutta control for thermoelectric power generation [92].The proposed model shows significant performance in terms of tracking accuracy, stability, and computational complexity. Additionally, M5P is evaluated against deep learning models for maximum power point (MPP) estimation in hybrid PV-TEG systems [80]. The proposed model shows faster tracking speeds, greater accuracy, and reduced need for periodic tuning. Furthermore, compared to the novel initialization technique for global maximum power point tracking [10] the proposed M5P model shows improved efficiency and robustness, particularly in terms of initialization speed and global search capability. A novel (MPPT) method using a PI discrete reverse-acting controller developed especially for wind power conversion systems is proposed in [63]. In this paper, an innovative intelligent and predictive (MPPT) method based on the M5P algorithm is proposed, which represents a considerable advancement in wind energy conversion systems. The key innovation lies in the development of a smart, programmable M5P algorithm, derived from the dataset of a fuzzy logic controller, specifically designed to address dynamic wind speed changes. The M5-Pruned algorithm offers excellent performance in terms of predictive capabilities, fast response, and adaptability to external disturbances. A major contribution of this work is the integration of a decision tree-based model into the wind power system, providing a visualized digital program that not only identifies specific operational challenges but also responds directly to sudden fluctuations. The model's digital decisions enable rapid (MPPT), as well as fast prediction and adaptation, resulting in improved accuracy and robustness. Unlike conventional methods, which are limited by static parametric gains and struggle to adapt to sudden system changes, the M5-Pruned algorithm dynamically adjusts to real-time conditions, presenting a more reliable, efficient, and adaptive solution for wind energy systems. This contribution showcases the potential of AI-driven control systems to develop energy optimization processes.

Table 4.1: Comparative final outputs of the proposed M5P algorithm with recent MPPT techniques

MPPT Method	**Ref**	**Complexity**	**Tracking Speed**	**Periodic Tuning**	**Accuracy**	**Stability**
P&O	[22]	Medium	Moderate	Yes	Moderate	Moderate
SMC	[23]	High	Fast	Yes	High	High
INC	[24]	High	Moderate	Yes	High	Moderate
PI Controller	[30]	Low	Medium	High	Medium	Medium
Runge Kutta Control for Thermoelectric Power	[27]	Moderate	High	Yes	High	Stable
Deep Learning	[28]	High	High	Rare	High	Stable
Optimizing conventional model global MPPT	[29]	Moderate	High	No	High	Stable
ANN	[20]	High	Fast	No	Medium	High
SSM-PSO	[21]	High	Fast	No	High	High
ACA	[25]	Medium	Moderate	Yes	High	Moderate
GWO	[26]	High	Moderate	No	Medium	High
FLC	[31]	High	Moderate	No	High	High
Proposed M5P	This work	Low	Fast	No periodic tuning	High (THD <1.83%)	Highly stable

4.2 Topological Modelling of System

4.2.1 Modeling of Wind Turbine

Wind speed is the actual prime mover of wind turbines. The wind performance is described by random values that can be defined by statistical parameters [28]. In this paper, a real wind speed is used as presented in Fig. 1 extracted via "Algiers, Algeria Weather History", it can be uploaded under this link: https://weatherspark.com/h/m/48929 /2024/2/Historical-Weather-in-February-2024-in-Algiers-AlgeriaFigures-Temperature

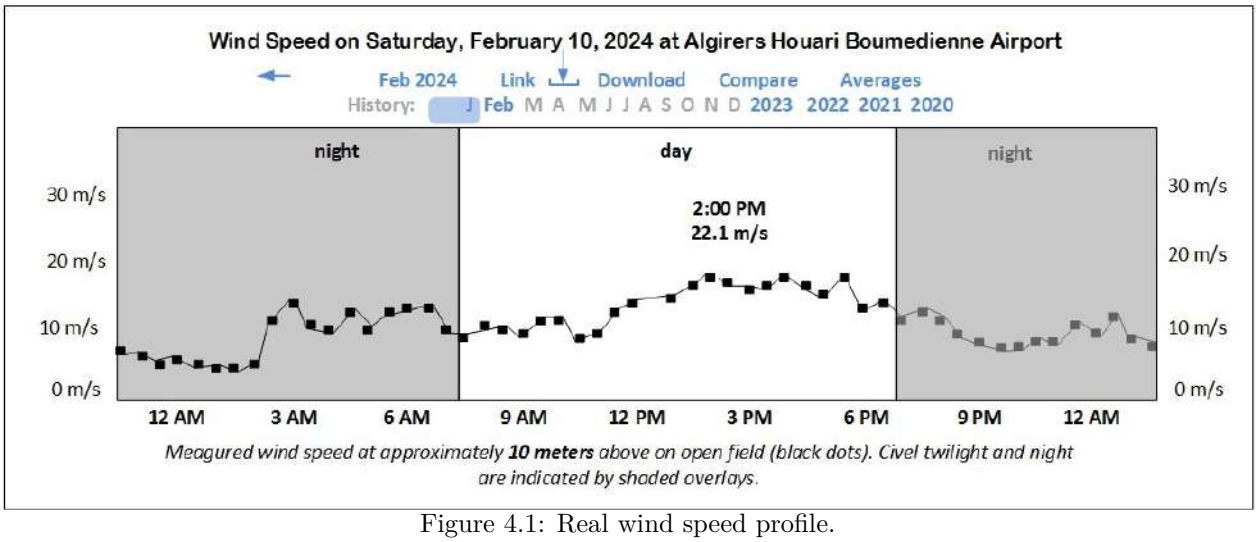


Figure 4.1: Real wind speed profile.

Wind speed causes the turbine blades rotation, which in turn creates mechanical power

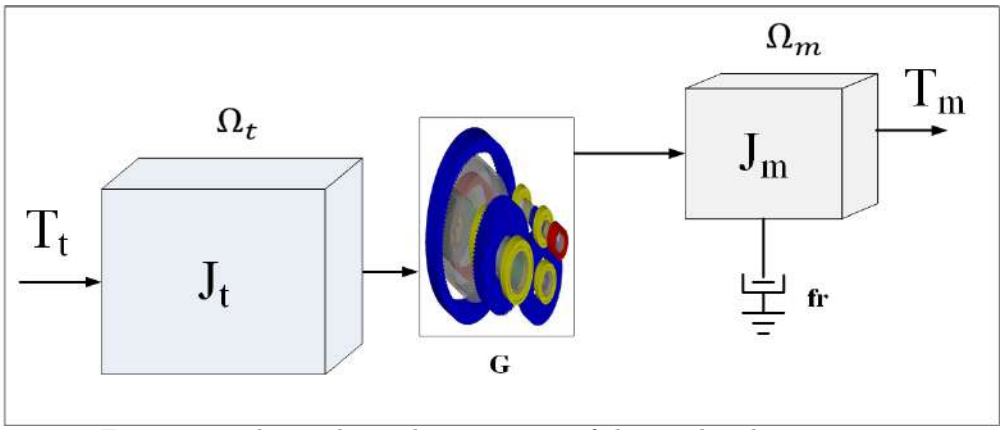


Figure 4.2: The mechanical components of the wind turbine system.

transferred to the shaft. P_t That can be written as follows:

$$P_t = \frac{1}{2} C_t(\lambda, \beta) \cdot \rho \cdot \pi R^2 V^3 \tag{4.1}$$

Where the relative speed lambda is defined as follows:

$$\lambda = \frac{R \cdot \Omega_t}{V} \tag{4.2}$$

Hence, the mechanical torque of the turbine axis is given by:

$$C_t = \frac{1}{2} \cdot C_P(\lambda, \beta) \cdot \rho \cdot \pi R^3 V^2 \tag{4.3}$$

Where the power coefficient is expressed as:

$$C_p(\lambda, \beta) = A_1 \left(A_2 \left(\frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3 + 1} \right) - A_3 \beta - A_4 \right) e^{-A_5 \left(\frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3 + 1} \right)} + A_6 \lambda \tag{4.4}$$

With A1 = 0.5109, A2 = 116, A3 = 0.4, A4 = 5, A5 = 21, A6 = 0.0068. Table 2 lists the specific parameters of wind turbines and DFIG. The adjustable turbine blades with length R are fixed and rotate with rotation speed. Ω_t and connected by multiplier gain G, which rotates the electric generator DFIG. The three blades can be modelled as a single system that represents all blade's mechanical characteristics [131]. Due to the turbine speed being very low, the friction coefficient can be negligible, thus the mechanical wind turbine model that consists of two mechanical masses can be described as displayed in Fig. 2. The multiplier gain that adapts the turbine speed with the generator speed is assumed robust and rigid and can be given by:

$$\Omega_m = G \cdot \Omega_t \tag{4.5}$$

The mechanical system presented in Fig. 2 is modelled by a dynamic fundamental model as follows:

$$\left(\frac{J_t}{G^2} + J_m \right) \frac{\mathrm{d}\Omega_m}{\mathrm{d}t} + f\,\Omega_m = T_m - T_{em} \tag{4.6}$$

where the generator rotation speed Ω_m is given by:

$$J\,\frac{\mathrm{d}\Omega_m}{\mathrm{d}t} \;=\; T_t \;-\; f_v\,\Omega_m \tag{4.7}$$

The total torque T_t and total inertia J_t of the rotating parts in system Fig. 2 are respectively defined as follows:

$$T_t = T_{mec} + T_m \tag{4.8}$$

$$J = \frac{J_t}{G^2} + J_m \tag{4.9}$$

4.2.2 Modelling of Doubly Fed Induction Generator

Under the dq reference frame, modelling the synchronous rotation of the speed $omega_m$ of DFIG and the electrical modelling of the generator can be represented as follows:

$$\begin{cases} V_{ds} = R_s I_{ds} + \frac{d\varphi_{ds}}{dt} - \omega_s \varphi_{qs} \\ V_{qs} = R_s I_{qs} + \frac{d\varphi_{qs}}{dt} + \omega_s \varphi_{ds} \\ V_{dr} = R_r I_{dr} + \frac{d\varphi_{dr}}{dt} - (\omega_s - \omega_r)\varphi_{qr} \\ V_{qr} = R_r I_{qr} + \frac{d\varphi_{qr}}{dt} + (\omega_s - \omega_r)\varphi_{qr} \end{cases} \tag{4.10}$$

Where R_s and R_r are the stator and rotor resistances of DFIG, respectively. $\phi_d s$,$\phi_q s$, $\phi_q r$ and $\phi_d r$ are the flux stator and rotor variables in the dq frame that can be modelled as follows:

$$\begin{cases} \varphi_{ds} = L_s I_{ds} + L_m I_{dr} \\ \varphi_{qs} = L_s I_{qs} + L_m I_{qr} \\ \varphi_{qs} = L_s I_{qs} + L_m I_{qr} \\ \varphi_{qr} = L_r I_{qr} + L_m I_{qs} \end{cases} \tag{4.11}$$

Where L_s, L_r and L_m are the stator, rotor and mutual inductors of the generator, respectively. The electromagnetic and mechanical torque of DFIG are given by the following equations:

$$T_{\mathrm{em}} = -\frac{3}{2}\frac{pL_m}{L_r}\left(\varphi_{ds} I_{qr} - \varphi_{qs} I_{dr}\right) \tag{4.12}$$

$$T_t = T_{\mathrm{em}} + J\frac{d\omega_r}{dt} + f_r \omega_r \tag{4.13}$$

Where p is the pair number of poles of DFIG.

The actual active power Ps and reactive power Qs of the DFIG's stator are modelled as follows:

$$P_s = \frac{3}{2}(V_{ds} I_{ds} + V_{qs} I_{qs}) \tag{4.14}$$

$$Q_s = \frac{3}{2}(V_{ds} I_{ds} - V_{qs} I_{qs}) \tag{4.15}$$

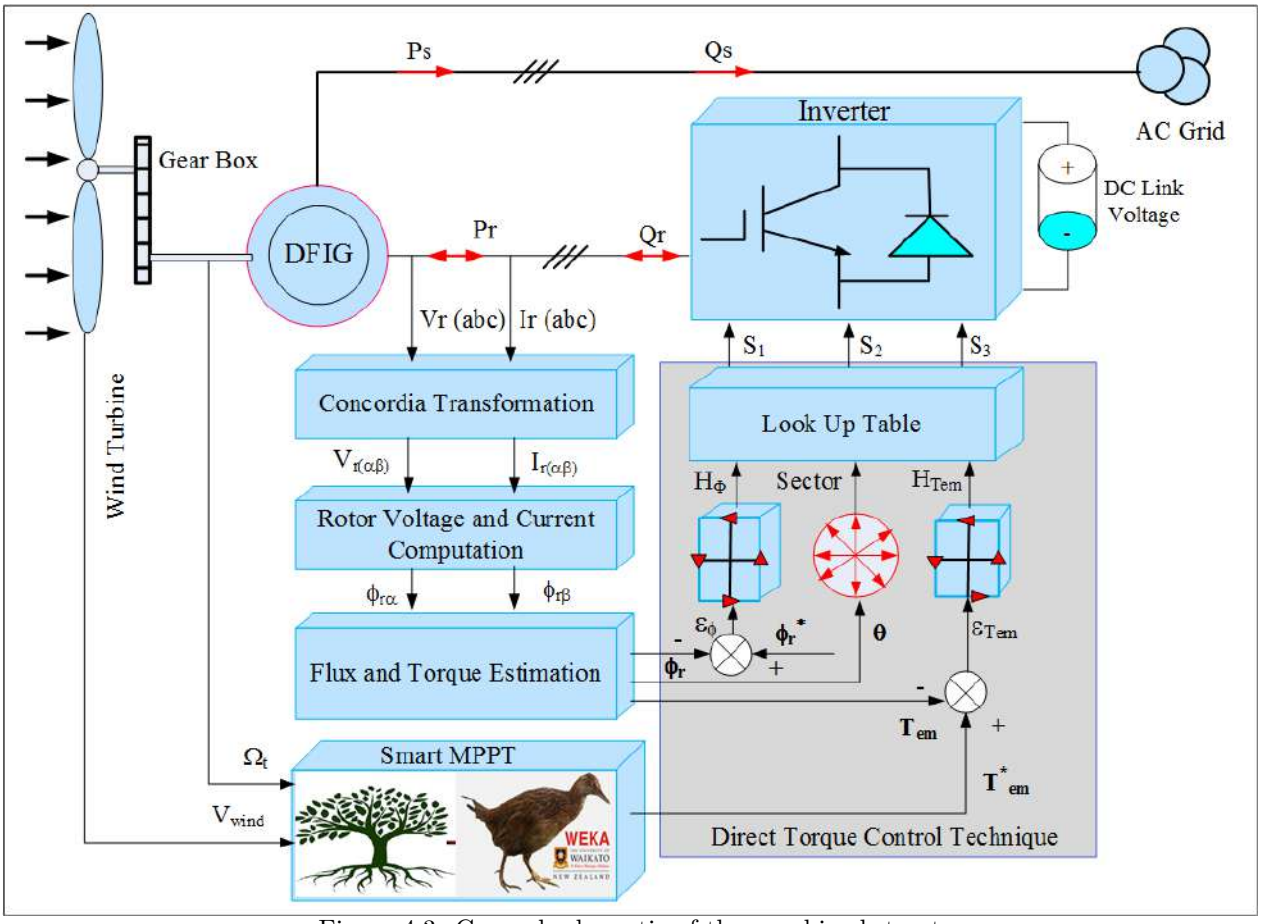


Figure 4.3: General schematic of the graphic abstract

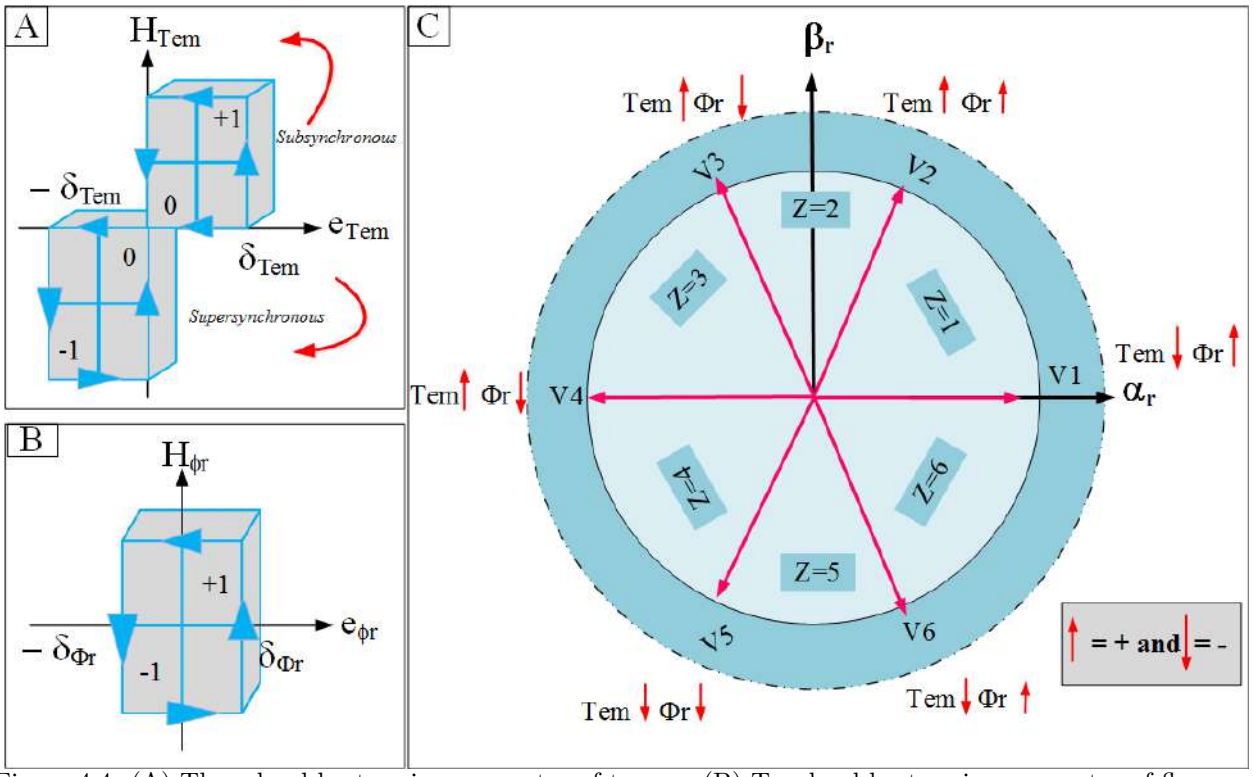


Figure 4.4: (A) Three-level hysteresis comparator of torque. (B) Tow-level hysteresis comparator of flux. (C) Schematic division process of sector.

4.2.3 Direct Torque Control Strategy Model

Fig.3 depicts the schematic of DTC for DFIG [100]. The Stator winding of DFIG is joined directly to the grid and the rotor is fed by three three-phase inverters. The major objective of the DTC is to control the rotor flux and the electromagnetic torque of the DFIG by selecting the most suitable voltage vector. As indicated in Fig. 4 (C), the rotor flux position is split into six sectors Z (1), Z (2) ..., and Z (6). There are also eight voltage vectors V0, V1..., and V7 considering that the vectors V0 and V7 are null. Depending on the space vector of the selected voltage and the synchronous speed of the DFIG, the stator the flux component ϕ_s can be defined as follows:

$$\phi_s = \frac{V_s}{\omega_s} \tag{4.16}$$

The DFIG torque can be described as a function of the angle between the stator and the rotor flux space vectors as follows:

$$T_{\text{em}} = -\frac{3}{2}\frac{pL_m}{\sigma L_s L_r}|\phi_s||\phi_r|\sin\delta \tag{4.17}$$

The coefficient of leakage is calculated as:

$$\sigma = 1 - \frac{L_m^2}{L_s L_r}$$

$$\frac{dT_{em}}{dt} = -\frac{3}{2}\cdot\frac{pL_m}{\sigma L_s L_r}|\varphi_s|\frac{d\left(|\varphi_r|\sin\delta\right)}{dt} \tag{4.18}$$

Therefore, according to model (10), control of torque can be achieved by adjusting the rotor flux vector. Where the amplitude of the rotor flux vector is defined as:

$$|\varphi_r| = \sqrt{\varphi_{\alpha r}^2 + \varphi_{\beta r}^2} \tag{4.19}$$

With:

$$\begin{cases} \varphi_{\alpha r} = \left(L_r - \frac{L_m^2}{L_s}\right) I_{\alpha r} + \frac{L_m}{L_s}\varphi_s \\ \varphi_{\beta r} = \left(L_r - \frac{L_m^2}{L_s}\right) I_{\beta r} \end{cases} \tag{4.20}$$

4.2.3.1 Hysteresis controller choice

The flux controller is established on a two-level hysteresis comparator while the torque controller operates with a three-level hysteresis comparator [89]. In the control flux side, to obtain fast dynamic performances, the selection of the hysteresis band with two levels is appropriate as indicated in Fig. 4 (B), the dynamic error variations of rotor flux are described as follows:

$$|\varphi_r^* - \varphi_r| \leq \Delta |\varphi_r|$$

The hysteresis controller is on three levels, enabling the torque control operation to rotate in two directions sub synchronous and super synchronous position as shown in Fig. 4. (A). The variation of the dynamic error of electromagnetic torque is expressed as follows:

$$|T_{em}^* - T_{em}| \leq \Delta |T_{em}|$$

4.2.3.2 The vector of voltages is determined by the hysteresis

controller outputs and by the sector Z(i), the space vector of the rotor flux is found [147]. Next, the rotor voltage selection is achieved according to Table 1.

Table 4.2: Look Up Table of DTC Technique

Hysteresis Output		**Sectors and Selected Voltages**					
H_F	H_T	**Z(1)**	**Z(2)**	**Z(3)**	**Z(4)**	**Z(5)**	**Z(6)**
1	1	V_2	V_3	V_4	V_5	V_6	V_1
	0	V_0	V_7	V_0	V_7	V_0	V_7
	-1	V_6	V_1	V_2	V_3	V_4	V_5
-1	1	V_3	V_4	V_5	V_6	V_1	V_2
	0	V_0	V_7	V_0	V_7	V_0	V_7
	-1	V_5	V_6	V_1	V_2	V_3	V_4

Z(i) = Zone, i=0,1,2,...,7, V_1=100, V_2=110, V_3=010, V_4=011, V_5=001, V_6=101, V_0=000, V_7=111

If the rotor flux is located in Z (1), voltage vector V2 is applied to raise the flux (HF =1) and torque (HT =1). Vector V6 is applied to increase the rotor flux (HF =1) and decrease the torque (HT = -1) in the same sector Z(1). As a generality, it can therefore, be said that if the rotor flux resides in the Z (i) sector, where i = 1, 2 ...6, applied voltage vectors Vk+1 and Vk+2 reduce the electromagnetic torque, while the vectors

Table 4.3: Specification of system parameters

Turbine Parameter			**Parameter of DFIG**		
Parameter	**Symbol**	**Value (Unit)**	**Parameter**	**Symbol**	**Value (Unit)**
Blade radius	R	3 (m)	Nominal power	P_n	4000 (W)
Number of blades	Blade	3	Stator-rated voltage	V_{1n}	400 (V)
Nominal wind speed	V	16 (m/s)	Rated current	I_n	5.8 (A)
Gearbox ratio	G	5.4	Rated DC-Link voltage	U_{DC}	514 (V)
Moment of inertia	J	0.3126 (Kg·m^2)	Stator inductance	L_s	0.005839 (H)
Viscous friction coefficient	F_r	0.00681 (N·m·s)	Rotor inductance	L_r	0.005839 (H)
Optimal speed ratio	λ	8.1 (rad)	Mutual inductance	L_m	0.1722 (H)
Sample time	T_s	$1e^{-5}$ (s)	Stator resistance	R_s	1.395 (Ohm)

Vk-1 and Vk-2 increase it. Moreover, the application of Vk+2 and Vk-2 declines the rotor flux, while Vk+1 and Vk-1 increase it [42].

4.3 Proposed MPPT Strategy for Wind Power Conversion

The amount of power output from a wind energy transformation system depends upon the accuracy with which the peak power points are followed by the MPPT controller irrespective of the type of generator utilized. The power retrieved from wind energy systems depends on the power set point traced by the MPPT technique and in the high wind speed region.

4.3.1 M5-Pruned Decision Tree Conception

4.3.1.1 Decision Tree

The decision tree approach arranges the dataset as a tree outlook consisting of roots, branches, and leaves. The recursion achievement of the most optimal outcome classifies the dataset values to carry out the prediction process by taking the following steps: Attribute selection into the root node, choosing the branch and adding the possible values to the branch, repeating this process in all branches of the tree with only the attribute that connects the branch [46]. To produce the most homogenous sheet, the purity criterion of the sheet is taken into account. The attribute that has the highest correlation is the best in the class distribution. Tree development must take place in two phases. The first one is the tree structure, where the data space is divided purely into subspaces in terms of class. The second phase is the pruning tree, which uses a criterion to remove the unrepresented branches (terminal parts) to achieve high predictive performance. After pruning, the learning process labelled the recent leaves based on the distribution of observations. The M5P decision tree algorithm deals with tasks that have high dimensions and is used for continuous and qualitative operations that have missed or normalized values. Hence, M5P is used for product classification, clustering, or association rules of individuals and objects. The M5P algorithm uses the (if-then) conditional form that can be carried out through each path of the tree from root to leaf as illustrated in Fig. 5. Thus, the fuzzy logic dataset was a suitable choice for improvement. To minimize the prediction of error, the M5P algorithm divides the dataset in each node depending on the chosen attribute. The prediction of error can be estimated for one node (i) by determining the standard deviation concept S_i. Thus, the standard deviation is defined as follows:

$$SDR = S_i - \sum_{k=1}^{C} \frac{N_k}{N_i} S_k \ldots \tag{4.21}$$

Where each node K is occupied by N_k examples, and (a) division of node (i) in C branches. The mean absolute error (MAE) is calculated as follows to reduce the error between the desired value and the actual value:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| Y_i - \hat{Y}_i \right| \tag{4.22}$$

Where $Y_i, \hat{Y}$ and n are the actual, predicted value and number of data points, respectively. While the square root of MAE is represented as follows:

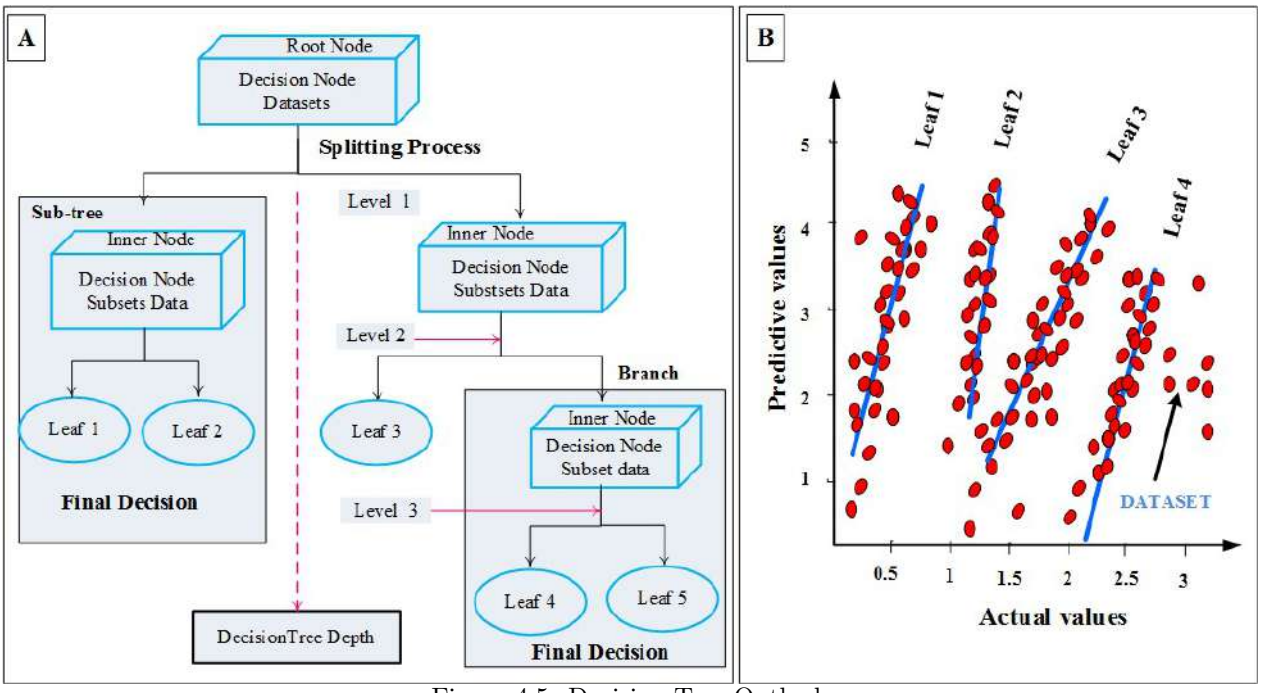


Figure 4.5: Decision Tree Outlook

$$RMAE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)^2} \tag{4.23}$$

To recognize the training quality, the coefficient factor (R) can be calculated as follows:

$$R = \sqrt{\frac{\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)^2}{\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)^2}} \tag{4.24}$$

4.3.2 Regularization of the Model

Regularization includes the construction of an average model to move from one leaf to another leaf of the tree. This process leads to discontinuities in predictions. Throughout the M5 framework, regularization starts by building a linear model for all the tree nodes. In the average model, the average weights are taken as predicted values as an example of the predictions in each model received at each node.

4.3.2.1 Attribute

The M5P decision tree algorithm manages the attributes via transformation from natural attributes into binary attributes using its linear model.

4.3.2.2 Missing Value

The versatile ability of the M5-Pruned algorithm can deal with the missing values via many technical methods involving: replacing the missing value with a default value as a

mean or median value using the imputation technique to another value in the dataset. Ignoring the missing value is another method based on ignoring the instance of the missing value, but this method can lead to less accuracy.

4.3.2.3 Pruning

Pruning in the tree algorithm is used to analyze the dataset to improve the performance of making a suitable decision. There are two types of pruning: pre-pruning and post-pruning [39]. In pre-pruning, the decision tree building is stopped when the pruning reaches a certain depth sufficient to make the final decision according to certain criteria. In post-pruning, the decision tree algorithm is trained until reaches its full depth, the repruning back in some nodes to remove the nodes that capture the noise to simplify the tree without lack of accuracy [115]. The proposed M5-Pruned model handles the noise issue in wind speed measurements by using its pruning mechanism, which allows the elimination of outside or noisy data points during the model training operation. By selectively pruning branches that do not significantly contribute to the predictive accuracy, the algorithm decreases the risk of overfitting to noise. Further, the algorithm creates a decision tree established on the most suitable attributes, leading to more stable predictions in the presence of noisy inputs. To further improve robustness, smoothing methods are applied to decrease the impact of abrupt oscillations in wind speed data. After the pruning and smoothing operations, the model can generalize well to unseen data while maintaining an accurate performance until under noisy environments.

4.4 Conventional MPPT Strategy

To present sufficient evidence, demonstrate the effective contribution and show the remarkable improvements of the proposed MPPT-M5P algorithm, a brief theoretical comparative presentation between MPPT based on PI, MPPT based on FLC and the proposed MPPT-M5P has been incorporated in this work.

4.4.1 MPPT Based on PI Controller

In order to prove the effectiveness of the proposed algorithm, it is important to present the comparative results. In this topic, the results of MPPT based on the PI controller [63] are added in the simulation section. The mathematical model of the PI controller can be presented as follows:

$$u(t) = K_P e(t) + K_i \int_0^t e(t)\, dt \tag{4.25}$$

In [41] a detailed MPPT is based on the PI controller. Fig. 8 presents the MPPT model based on the PI controller.

4.4.2 MPPT based on Fuzzy Logic Controller

Fuzzy logic is a framework of modelling that deals the complex and ambiguous situations by using a degree of truth to make decisions. The truth values are taken as a numerical

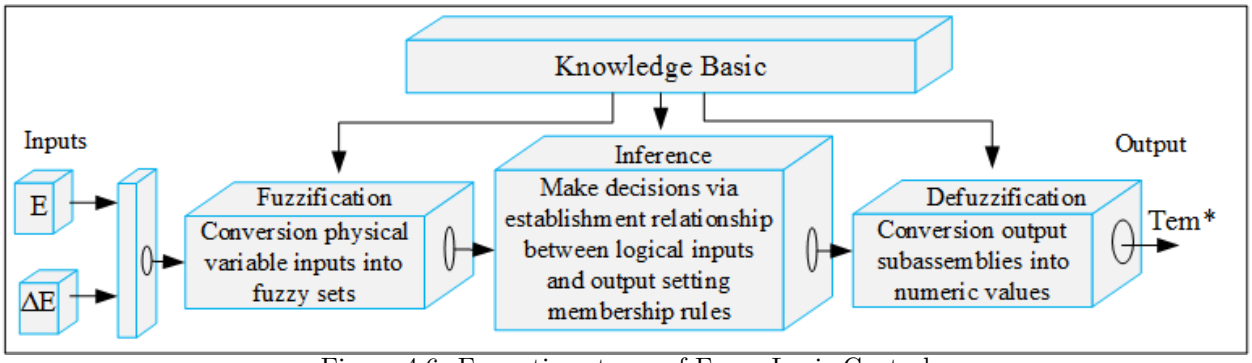


Figure 4.6: Formation stages of Fuzzy Logic Control

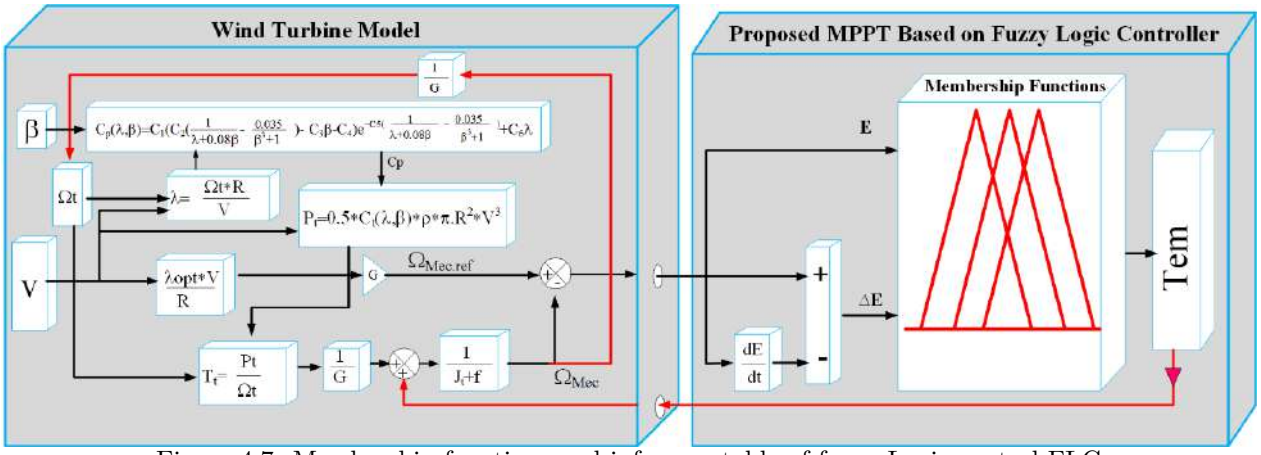


Figure 4.7: Membership functions and inference table of fuzzy Logic control FLC

field between 0 and 1, where 0 represents absolute falsity and 1 indicates absolute truth, unlike the classical (Boolean) logic that is based on binary values (0 or 1) representing (true or false) levels [64]. Fig. 6 shows the three main stages of forming the fuzzy controller: Fuzzification, inference, and defuzzification. Fig.7 represents the general diagram of the MPPT-FLC technique. The embedded FLC in the MPPT strategy is of the Mamdani type with 7*7 rules. The fuzzy controller inputs are the mechanical speed error $E_(\omega_{mec})$and its derivative, while the output is the reference direct torque T_em^*. Eqs (17) and (18) represent the error of reference electromagnetic torque and its derivative, respectively:

$$E_{\Omega\text{mec}} = \Omega^*_{\text{mec}} - \Omega_{\text{mec}} \tag{4.26}$$

$$\Delta\Omega_{\text{mec}} = \Delta\Omega_{\text{mec}}(k) - \Delta\Omega_{\text{mec}}(k-1) \tag{4.27}$$

Trapezoidal and triangular shapes are selected as membership functions of the FLC as shown in Fig. 8. To formulate the fuzzy controller rules, seven linguistic variables are selected for each input and output (E, E, and Idc*), which are: NB is Negative Big, NM is Negative Medium, NS is Negative Small, ZE is Zone Zero, PS is Positive Small, PM is Positive Medium, and PB is Positive Big. According to the development stages of error and its derivative either ascending or descending, the output decision of the rule is chosen as shown in Fig. 8.

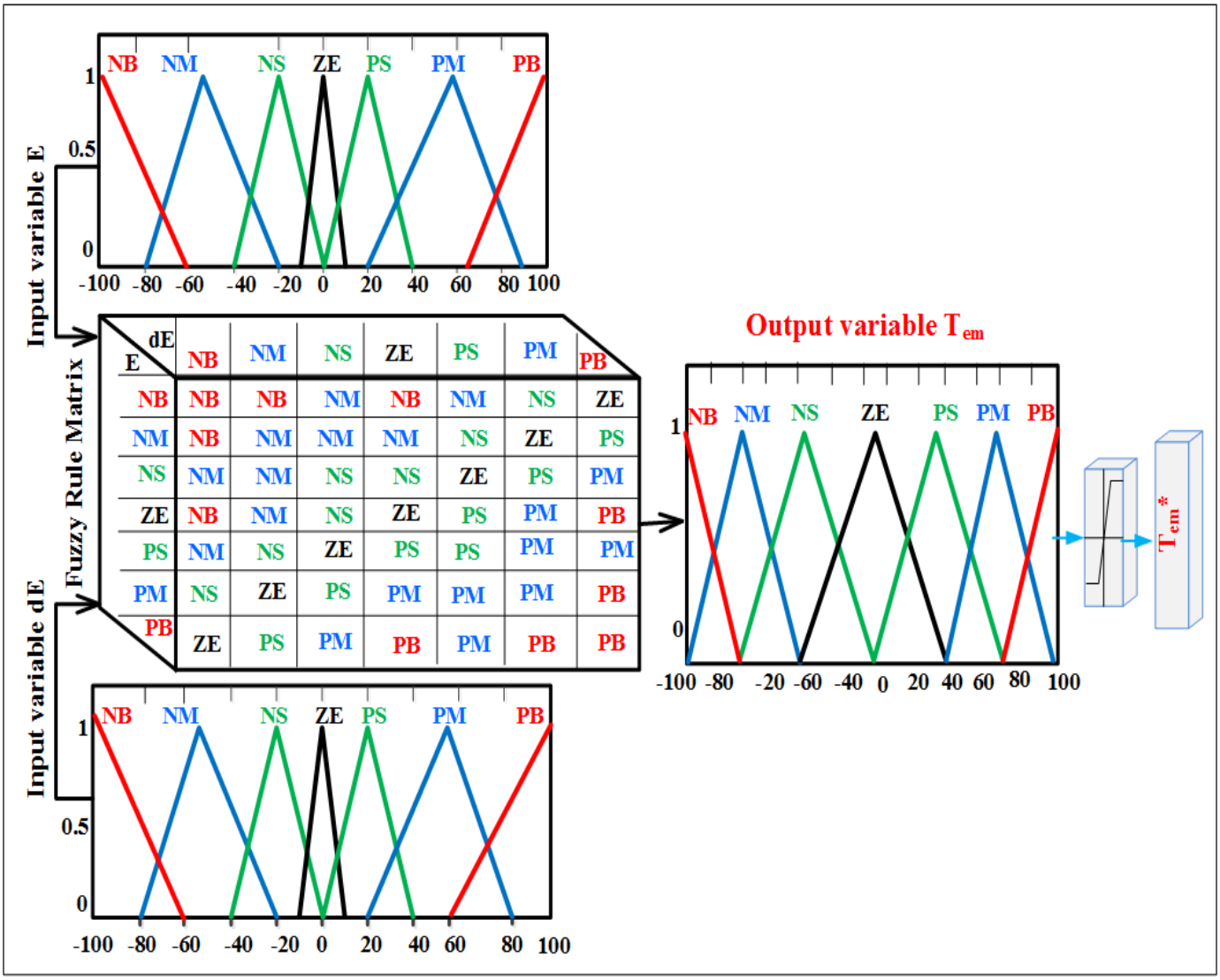


Figure 4.8: Membership functions and table of fuzzy Logic control FLC

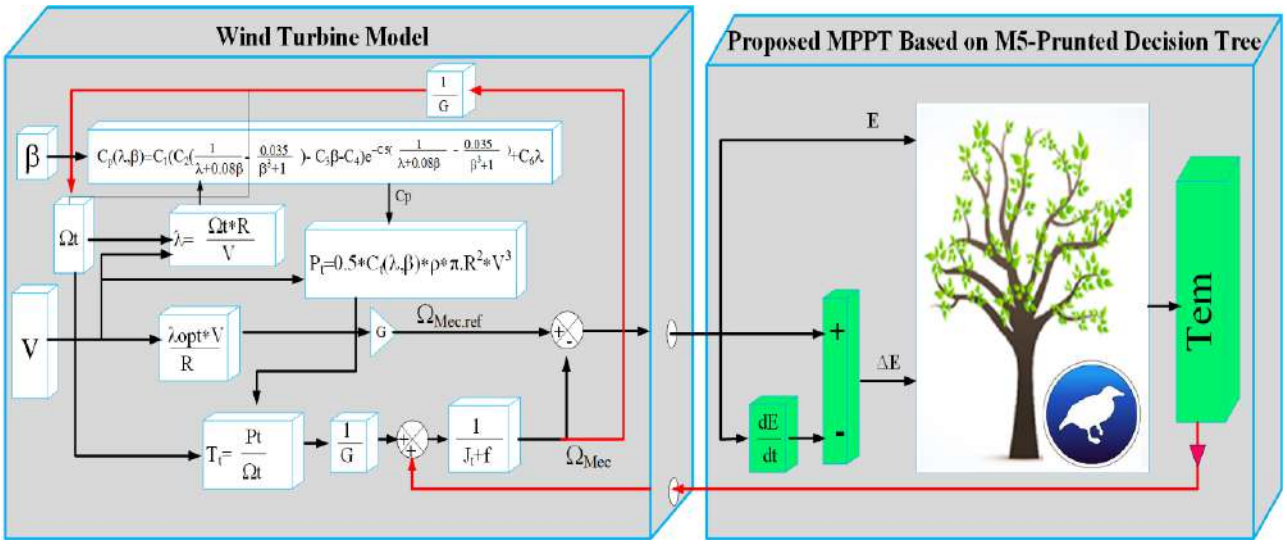


Figure 4.9: Proposed MPPT based on M5-Pruned Algorithm

4.4.3 Smart MPPT Strategy Based on Proposed M5-Pruned Algorithm

In wind energy systems, the most important issue that requires an accurate algorithm is the MPPT topic, because wind power is the essential supply for the whole system. Therefore, this area received great attention in our research and we are keen to present a new and effective strategy based on artificial intelligence (AI) to keep pace with modern development. The integration of AI into wind energy control represents a new addition to the field of energy control, especially with the rapid progress of AI in various fields. The M5-Pruned algorithm represents one of the most important AI algorithms currently because it is characterized by high capacity, effective performance, and quick prediction. In addition, it is distinguished by its simple structure, ease of integration into control systems, and clarity of formalism. It provides us with a digital program and a flowchart in the form of a decision tree as shown in Figs. 10 and 11, which explains how to deal with the database. Hence, to overcome the wind speed fluctuations that cause a waste of the available wind energy, avoid the significant defects of the conventional MPPT techniques, maximize the wind turbine outcome power as well and raise the efficiency of the wind turbine performance, the MPPT strategy based on the smart, powerful, efficient and robust M5-Pruned algorithm has been proposed. After a deep search, the M5-Pruned algorithm is adopted and inserted in the MPPT strategy as shown in Fig. 9 to overcome the conventional MPPT defects. The prediction ability of the proposed algorithm comprehends the fluctuations of the wind speed and benefits as much as possible from wind energy under sudden changes and saves the high value of MPP before the sudden change affects the entire system. Not only that, but it also has smart capacities for autonomous adaptation to future changes that may occur. Fast learning that takes only a few seconds, nonlinear model, predictability and robustness are significant characteristics of the proposed M5P model providing more accurate and efficient tracking of the maximum power point (MPP) under varying operating conditions. Fig. 12 illustrates the dataset management processes.

Figure 10 shows a step-by-step breakdown of the data flow, including the integration details of WEKA and Matlab. Figure 10 involves the main steps of generation of the proposed M5-pruned algorithm:

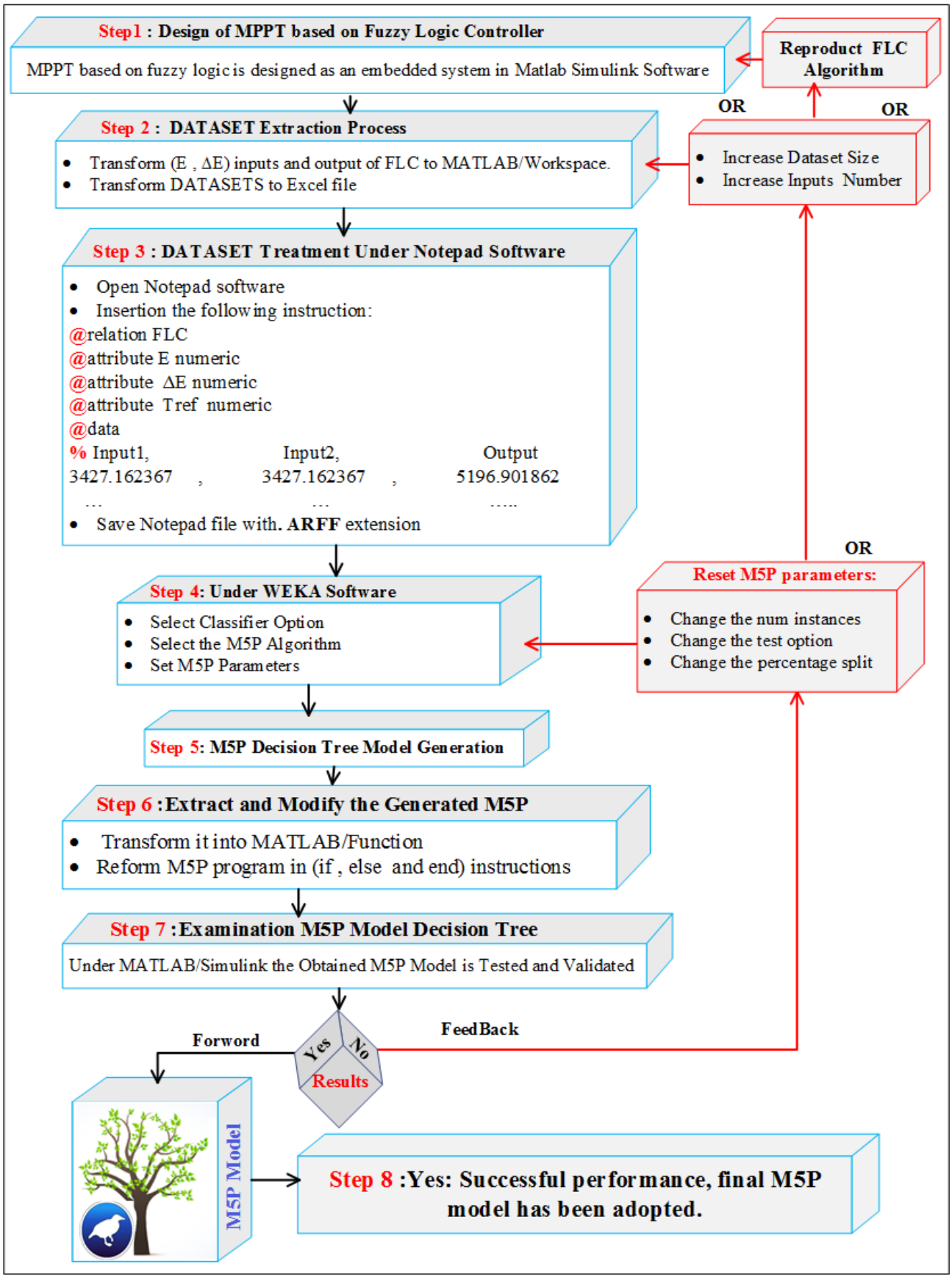


Figure 4.10: Dataset Management Process.

1. **Data Collection:** This is the first step where raw data is gathered from sensors of error E and derivative error of wind speed and output of FLC controller in the MPPT block. This stage aims to capture the real-world values needed for analysis and control.
2. **Preprocessing:** In this stage, normalization, data imputation, or filtering processes are applied because raw data often contains noise and missing values. The purpose is to ensure that the data is in an appropriate design and is ready for feature extraction and modelling.
3. **Feature Extraction (WEKA):** In this phase, WEKA (a machine learning tool) is operated to extract the most relevant attributes from the preprocessed data. Feature extraction involves selecting or transforming variables that are most significant for building the M5-Pruned model. This step aims to reduce data dimensionality and focus on significant inputs that influence the system's performance.
4. **M5-Pruned Model Training (WEKA):** WEKA utilizes the extracted features to train the M5-Pruned algorithm. This algorithm generates the decision tree, where the leaves are linear regression models that predict output variables. The predictive model is used to make real-time decisions within the control system.
5. **Model Export to Matlab:** The generated model is exported to Matlab. Matlab is used for real-time simulation and control purposes.
6. **System Simulation (Matlab):** The exported model is used in Matlab to simulate the performance of the whole system. In this step, performance evaluation and forecast of how it will behave under various conditions are achieved in order to validate the accuracy of the model and its effectiveness in controlling the system.

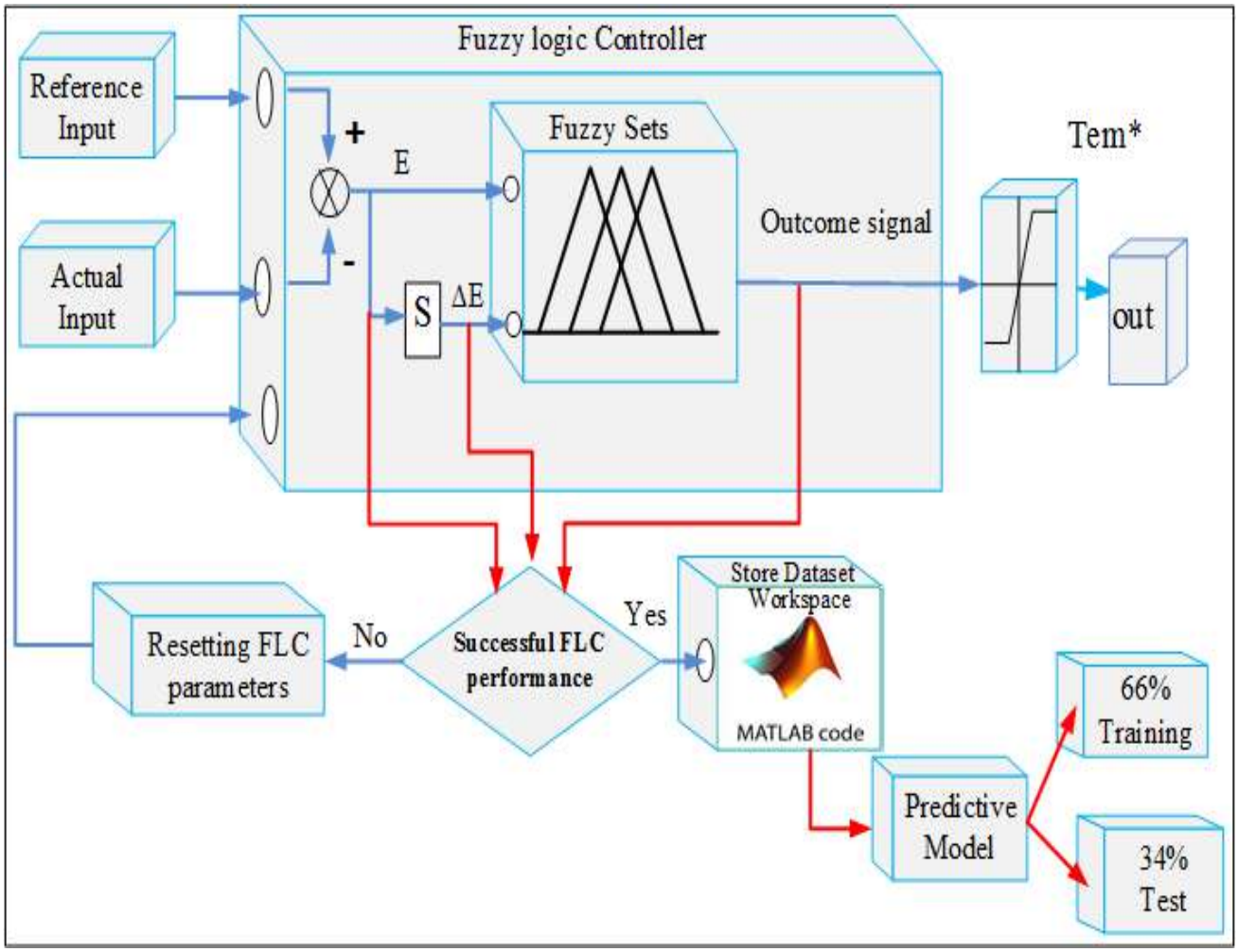


Figure 4.11: Dataset extraction methodology via FLC

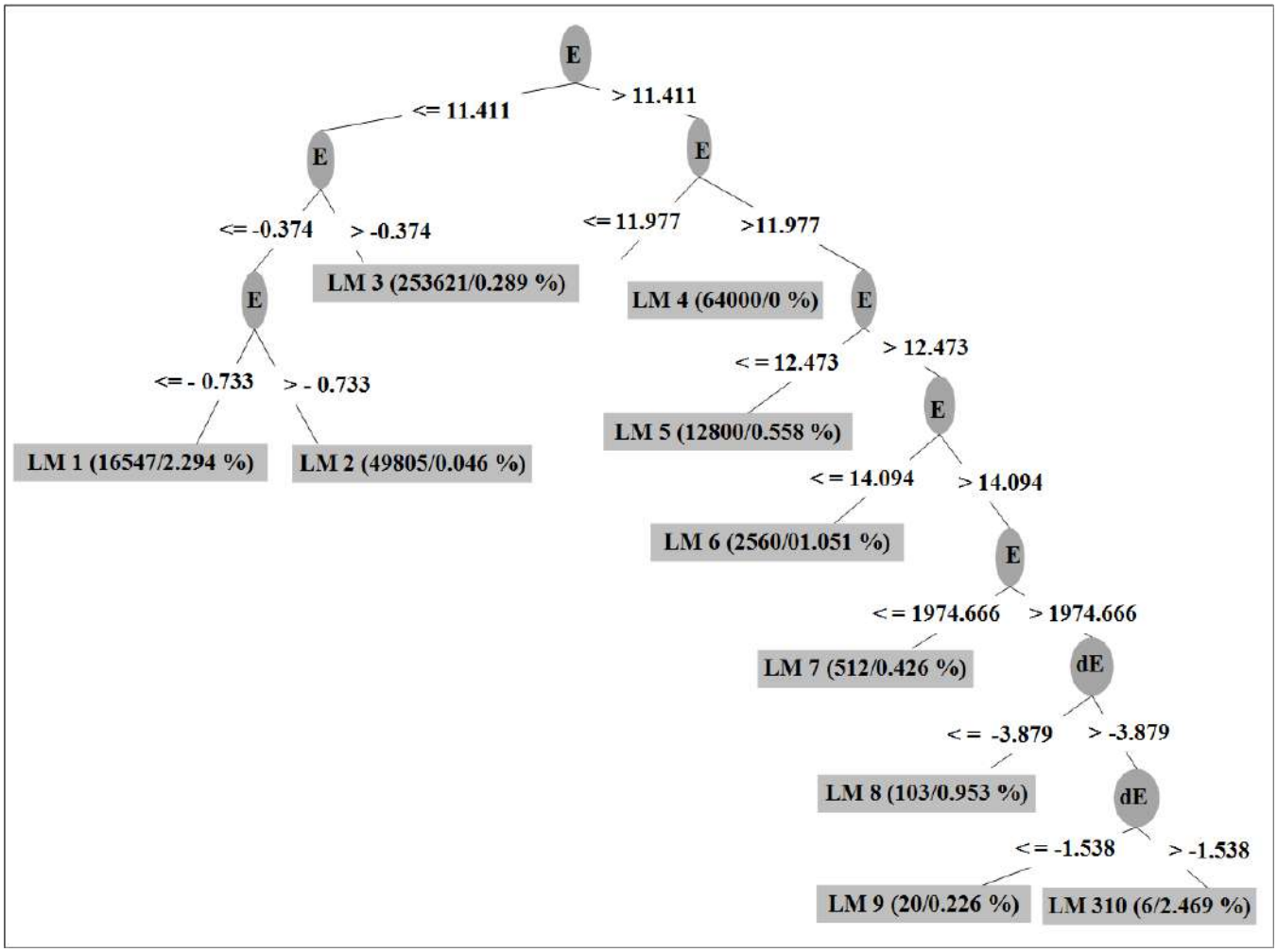


Figure 4.12: M5-Pruned decision tree algorithm extracted via WEKA software

A

```
=== Run information ===
Scheme: weka.classifiers.trees.M5P -M 4.0 -num-decimal-places 4
Relation :    FLC
Instances :   400001
Attributes :  3
              E, dE, C
Test mode:    evaluate on training data
=== Classifier model (full training set) ===
M5 pruned model tree: (using smoothed linear models)
E <= 11.411:
|  E <= -0.375:
|  |  E <= -0.733: LM 1 (16574/2.294%)
|  |  E > -0.733: LM 2 (49805/0.046%)
|  E > -0.375: LM 3 (253621/0.289%)
E > 11.411:
|  E <= 11.977: LM 4 (64000/0%)
|  E > 11.977:
|  |  E <= 12.473: LM 5 (12800/0.558%)
|  |  E > 12.473:
|  |  |  E <= 14.094: LM 6 (2560/1.051%)
|  |  |  E > 14.094:
|  |  |  |  E <= 1974.666: LM 7 (512/0.426%)
|  |  |  |  E > 1974.666:
|  |  |  |  |  dE <= -3.879: LM 8 (103/0.953%)
|  |  |  |  |  dE > -3.879:
|  |  |  |  |  |  dE <= -1.538: LM 9 (20/0.226%)
|  |  |  |  |  |  dE > -1.538: LM 10 (6/2.469%)
LM1=1.5024 * E + 0.0001 * dE + 1.3306;
LM2=0.0007 * E + 0.0001 * dE - 0.0259;
LM3=0.0001 * a + 0.0001 * dE - 0.0061;
LM4=0 * E + 0.0006 * dE - 0.0001;
LM5=0 * E+ 0.0034 * dE + 0.0325;
LM6=0.0001 * E + 0.0174 * dE + 0.6201;
LM7=0.0003 * E + 0.0847 * dE + 0.7092;
LM8=0.0008 * E + 0.3629 * dE + 2.2617;
LM9=0.0008 * E + 1.0355 * dE + 5.7637;
LM10=0.0008 * E + 1.5134 * dE + 6.5922;
Number of Rules: 10
Time taken to build model: 6.08 seconds
=== Evaluation on training set ===
Time taken to test model on training data: 1.13 seconds
=== Summary ===
Correlation coefficient                  1
Mean absolute error                      0.0195
Root mean squared error                  0.0775
Relative absolute error                  47.1531 %
Root relative squared error              0.6766 %
Total Number of Instances                400001
```

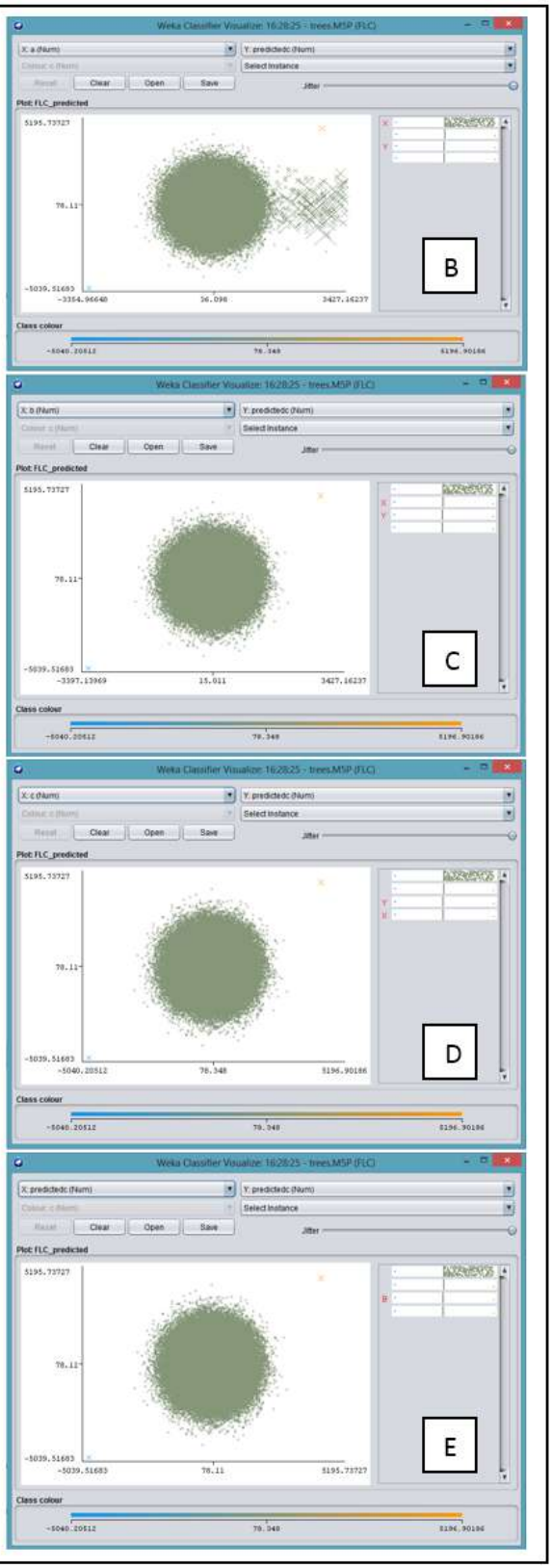


Figure 4.13: M5-Pruned Decision tree algorithm extracted via WEKA software. (A) Digital program of M5P algorithm. (B) Classification of input's error data. (C) Classification of input's derivative error data. (D) Classification of output data. (D) Classification of predictive output data.

Table 4.4: Comparative Performance Analysis of Control Methods in Renewable Energy Systems

Method	**Energy Efficiency (%)**	**Energy Savings (%)**	**Operational Cost Reduction (%)**	**Case Study**	**Ref**
M5-Pruned Algorithm	96.8	12.5	15.2	This work	This work
Conventional PI Control	89.5	5.5	7.3	Standard PI-based control for the same solar PV system shows lower efficiency due to slower dynamic response and higher switching losses.	[43]
Fuzzy Logic Controller	92.3	7.8	9.1	Fuzzy Logic-based control shows moderate improvement over PI but lower performance compared to M5-Pruned, especially under rapidly changing conditions.	[44]
Neural Network Control	94.2	10.1	11.8	Neural Network control performs well but still falls short of the optimization and reduced complexity offered by the M5-Pruned algorithm.	[45]

4.5 Simulation Results

Comparative simulation results are crucial in evaluating the performance of a proposed system or algorithm. To validate insight and understand the underlying mechanism of the proposed MPPT-M5P algorithm, the comparative simulation results between proposed MPPT-M5P, MPPT-PI and MPPT-FLC have been achieved.

fThe wind speed is the main input of the system, to ensure the simulation accuracy, confidentiality and validity, realistic and reliable input data of the real wind speed is used, which represents the real environmental variations, and actual calibrated measurements. Fig. 4.14 shows the real wind speed profile with simulation time [0 1] that equals [0 24^h] in the real profile. Fig. 14 was taken on Saturday, February 1, 2024, at Algiers Houari Boumedienne Airport.

4.5.1 Outputs Simulation Results of Wind Power Turbine

In order to provide empirical evidence, support the statistical analysis process, contribute to generalization, and enhance communication, the comparative results are illustrated. The mechanical speed and power of the turbine is a picture of the wind speed as shown in Figs. 4.15 and 4.16, respectively. It is clear that the mechanical speed and power of the turbine correspond to the wind speed profile, which proves the accurate performance of the mathematical parametric performance of the turbine. In the transient state during t= [0 0.015] s, it can be noted that the proposed MPPT-M5P strategy achieved a fast response t_{M5P}=0.001s compared with the conventional MPPT-PI and MPPT-FLC techniques t_{PI}=0.01s and t_{FLC}=0.023s, respectively.
Fig. 4.17 represents the relative speed ratio λ (rad) curve, which shows that the turbine's performance varies under different operating conditions. Despite the real wind speed used being variable, λ showed almost constant behaviour compared to the conventional MPPT-PI and MPPT-FLC. It is clear that the proposed MPPT-M5P algorithm curve is more stable than the other embedded models of conventional MPPT techniques. MPPT-M5P strategy was the closest performance to the optimal value of λ o_{pt}=8.1m, which indicates the effectiveness and robustness of the proposed MPPT-M5P strategy. The power coefficient of the wind turbine is a fundamental parameter to analyze the performance, it represents the wind turbine's efficiency in converting the kinetic energy of the wind into mechanical or electrical power. It determines the turbine's ability in power generation. Fig. 4.18 shows the comparative results of the power coefficient; it is clear that the proposed MPPT-M5P model is a fast dynamic response to the desired level. It can be observed that the proposed algorithm was the most stable and free of significant ripples compared to MPPT-PI and MPPT-FLC techniques. Hence, after the analysis process of the obtained data, it was found that the proposed M5P model proved its efficiency and prediction abilities with the variable conditions of wind speed and kept the most stable performances compared with the other incorporated MPPT techniques in this paper.

4.5.1.1 Output simulation results of generator

In this section, the outcome findings of DFIG have been presented in order to show the power performance injected into the electrical grid. Figs. 4.19, 4.20, and 4.21 show

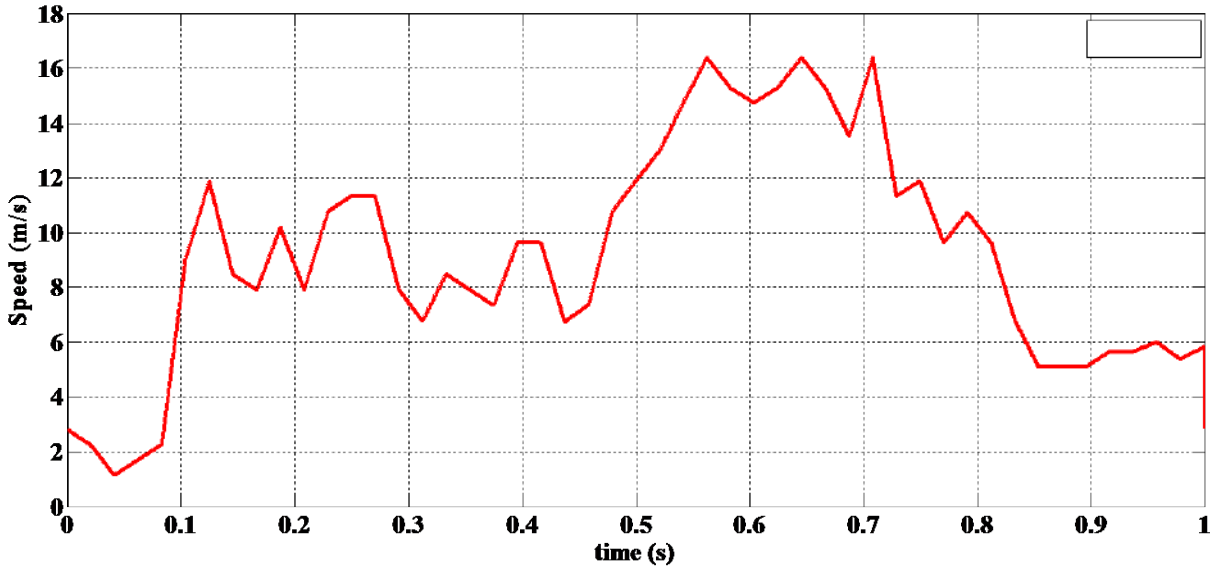


Figure 4.14: Real wind speed profile on Saturday, February 10, 2024, at Algiers Houari Boumedienne Airport

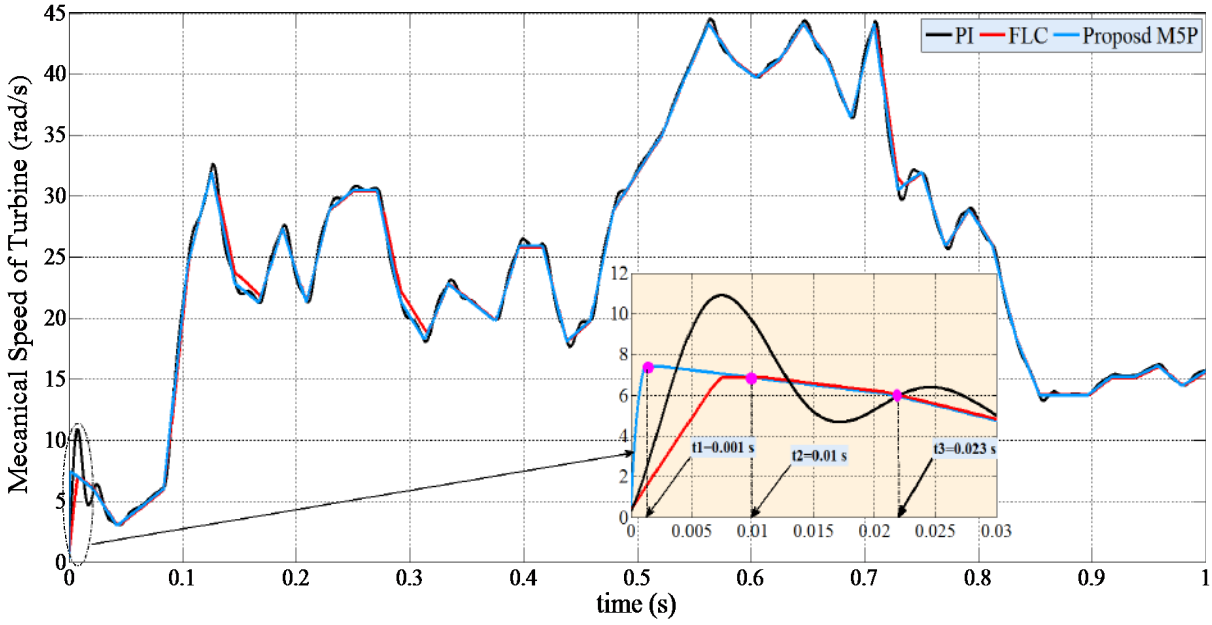


Figure 4.15: Comparative outputs for the mechanical speed of the turbine

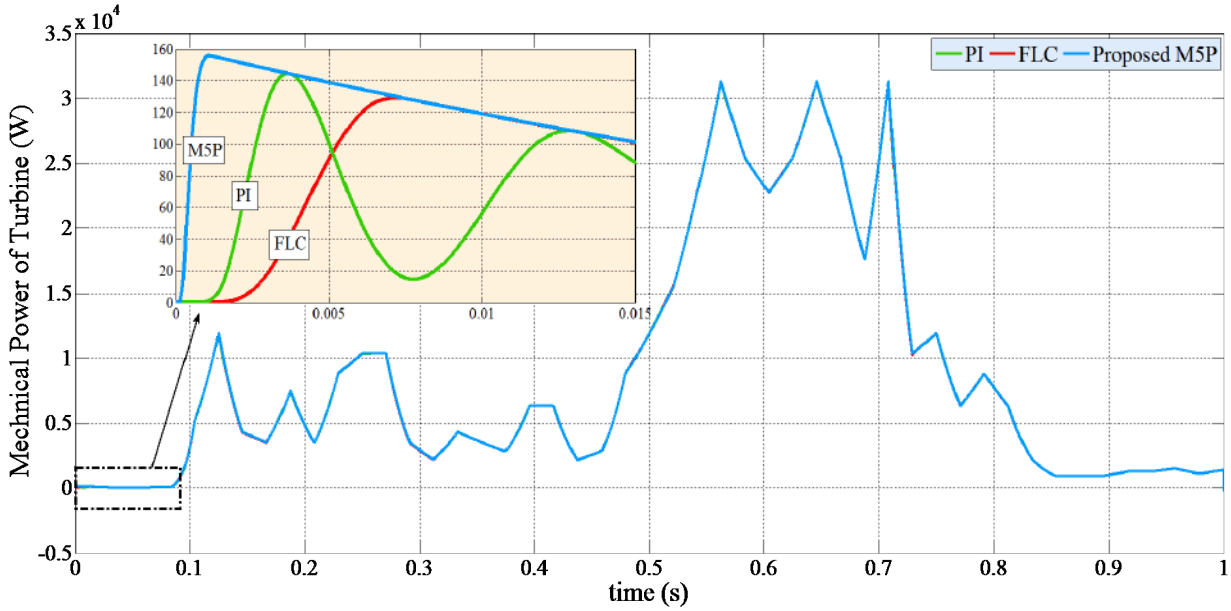


Figure 4.16: Comparative outputs of the mechanical speed of generator DFIG

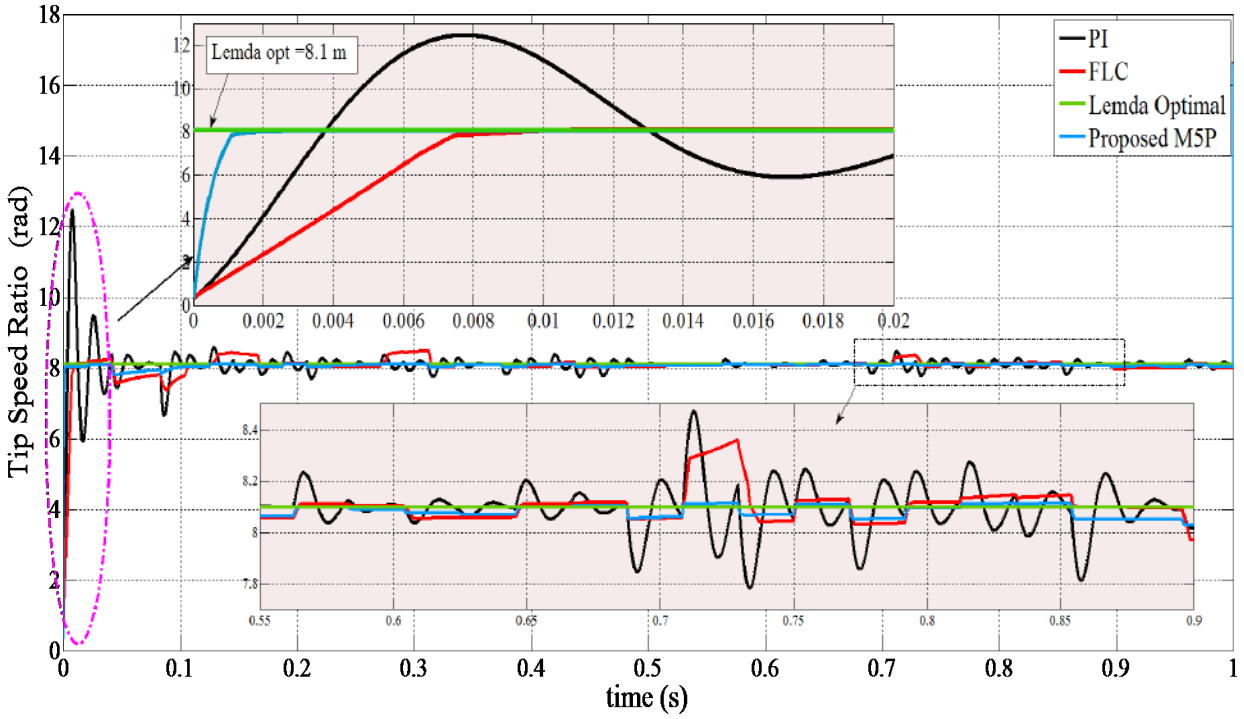


Figure 4.17: Comparative outputs of tip speed ratio $\lambda anditsoptimalvalue$

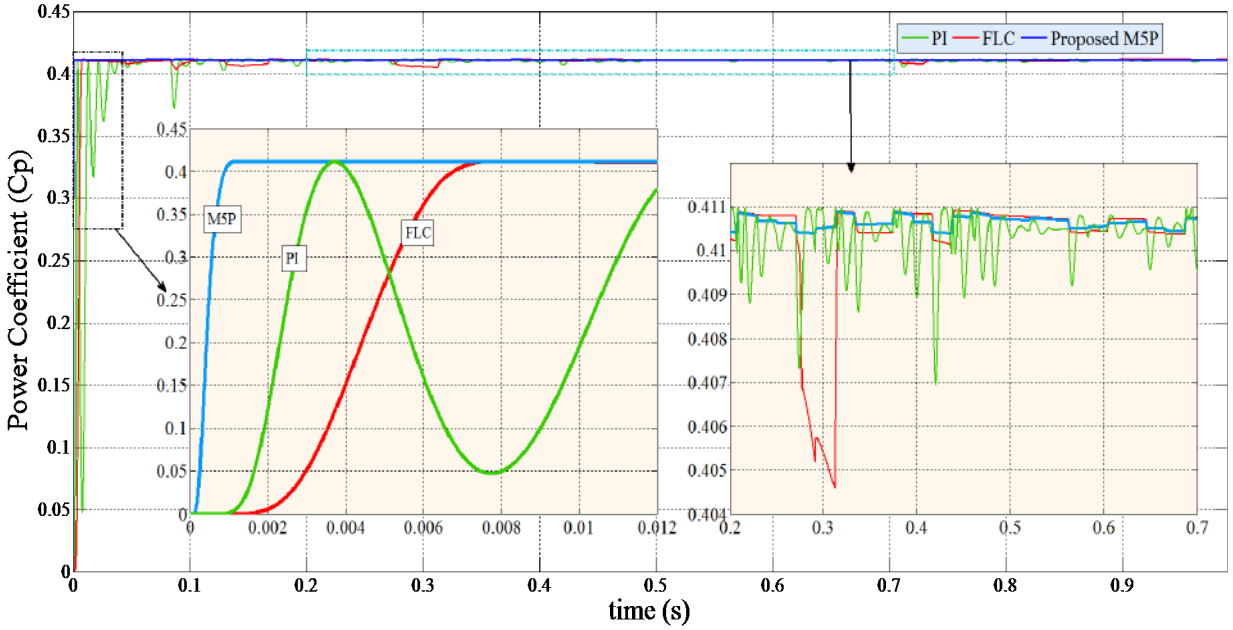


Figure 4.18: Comparative outputs coefficient power Cp

comparative results of the mechanical speed, flux and mechanical torque of DFIG, respectively. It can be seen that the proposed algorithm achieves an excellent performance, stable and free of ripples, compared to the other algorithms.

It can be observed also that the proposed algorithm was the quickest compared to its reference. The proposed MPPT-M5P keeps the most stable performance, although the wind speed performance is variable. Figs. 4.22 (A and B) shows the stator-generated active and reactive powers of the generator. It can be noted that the proposed model archives an excellent value of active power performance free of oscillations.

The efficiency of the proposed algorithm can be observed throughout the analysis of the reactive power of the system. It is clear that the proposed model achieves a unity power factor almost equal to 1→ (Qs=0). That means a purity injected active power into the electrical network.

Fig. 4.23 (A, B and C) shows the stator-generated currents of DFIG. It can be seen that the current performance is changed in response to changes in wind speed, which proves the consistency of the control system.

To justify the good performance of the proposed model compared to the other incorporated techniques. The THD profile is shown, where it found that the THD_{M5P} =1.83% during five cycles, which is less than the THD_{PI} and THD_{FLC} 1.93% and 1.92%, respectively, as shown in Fig. 4.24 (A, B, C).

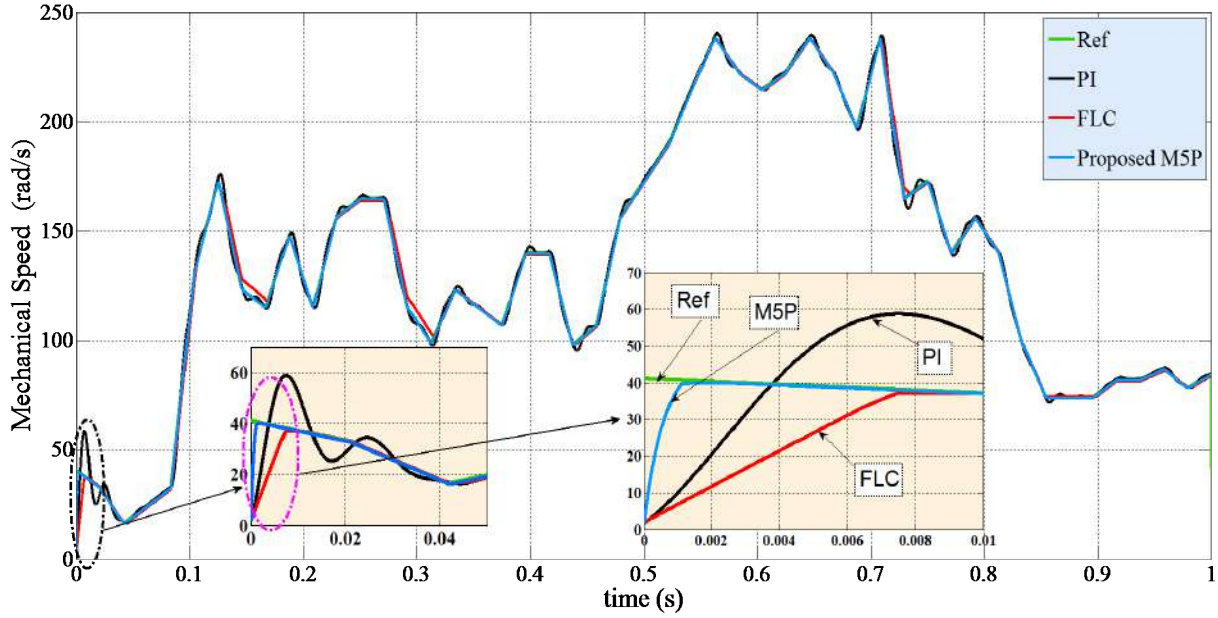


Figure 4.19: Comparative outputs of the mechanical speed of generator DFIG

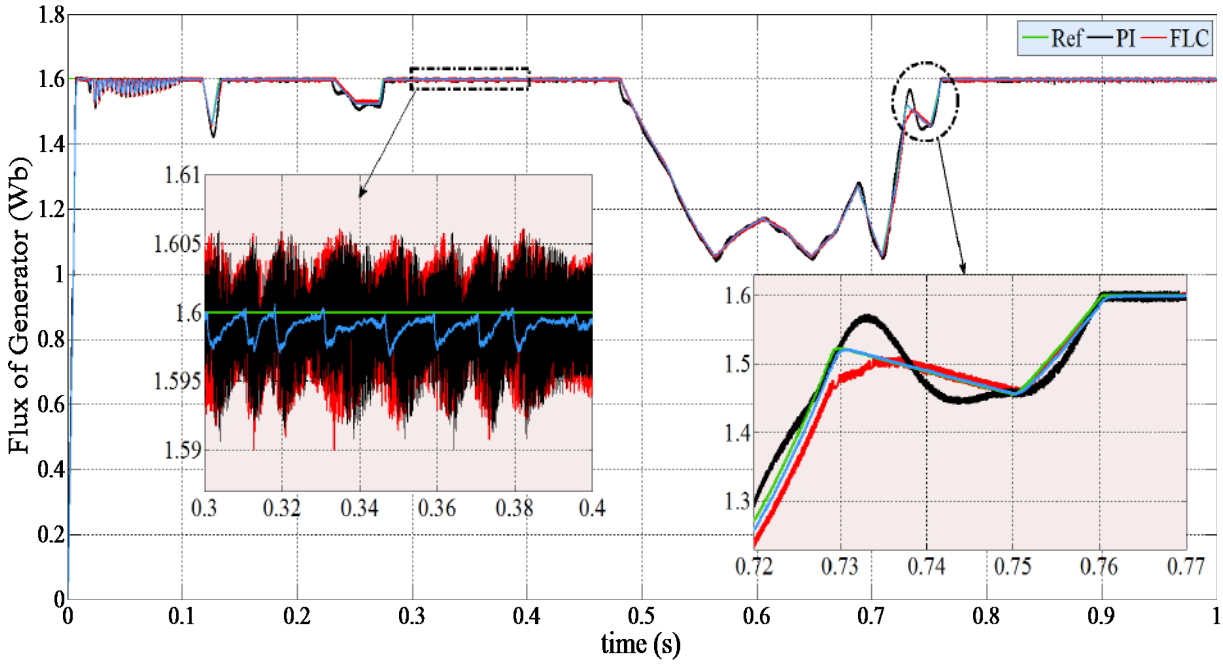


Figure 4.20: Comparative results of the flux of generator DFIG

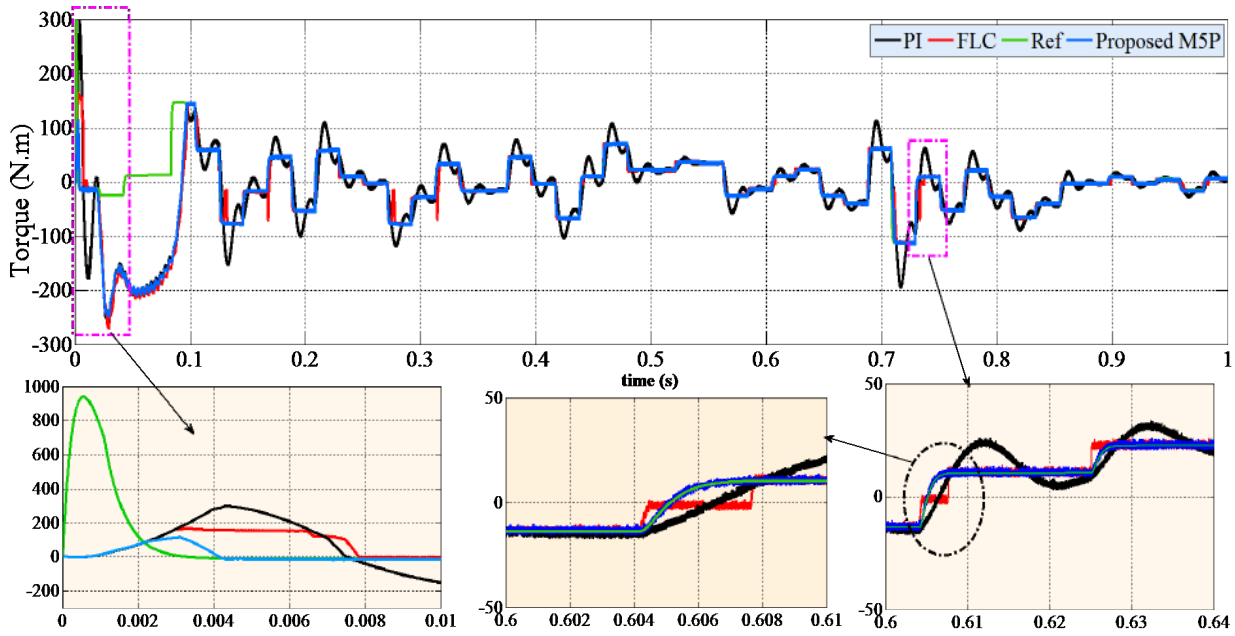


Figure 4.21: Comparative outputs of the mechanical torque of generator DFIG

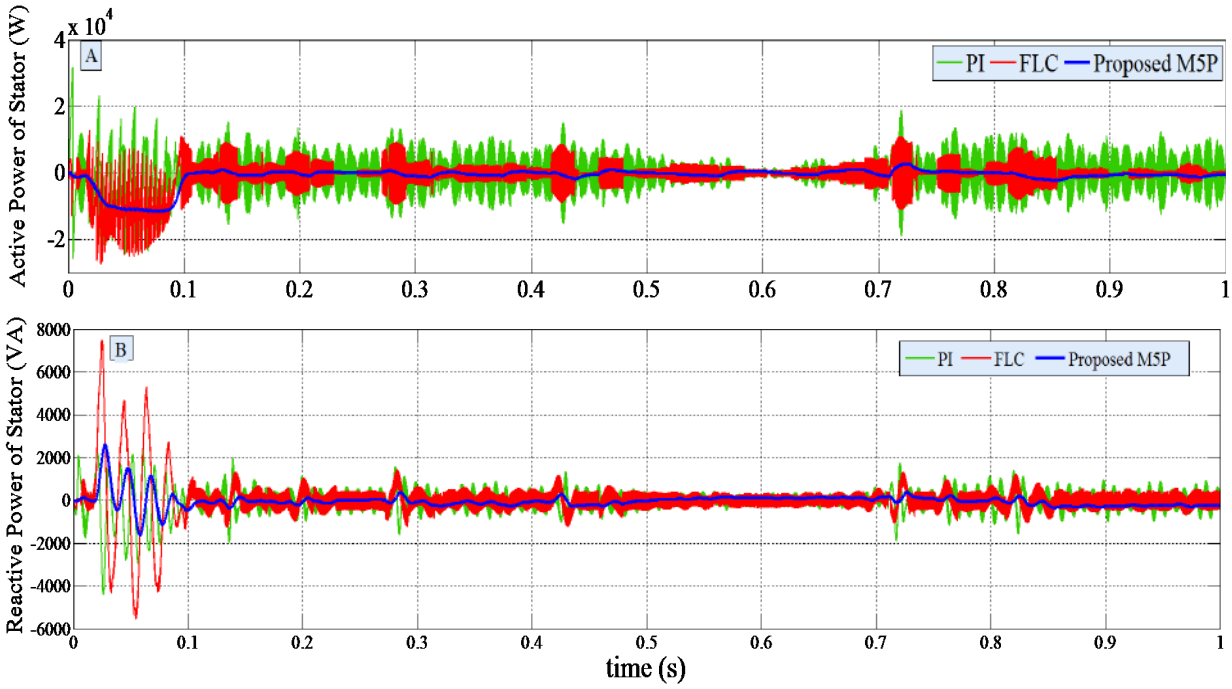


Figure 4.22: Fig 22. Comparative results of active and reactive powers of generator DFIG

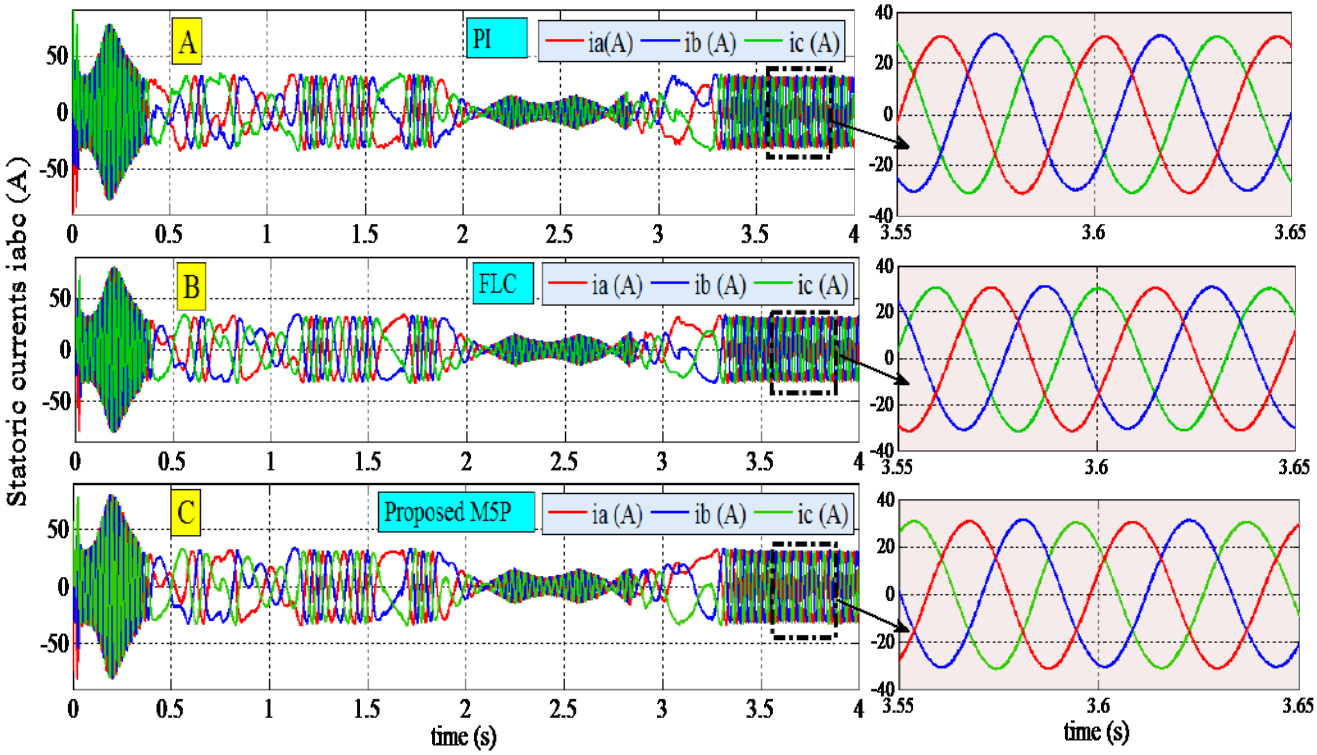


Figure 4.23: Comparative results of stator currents of generator DFIG

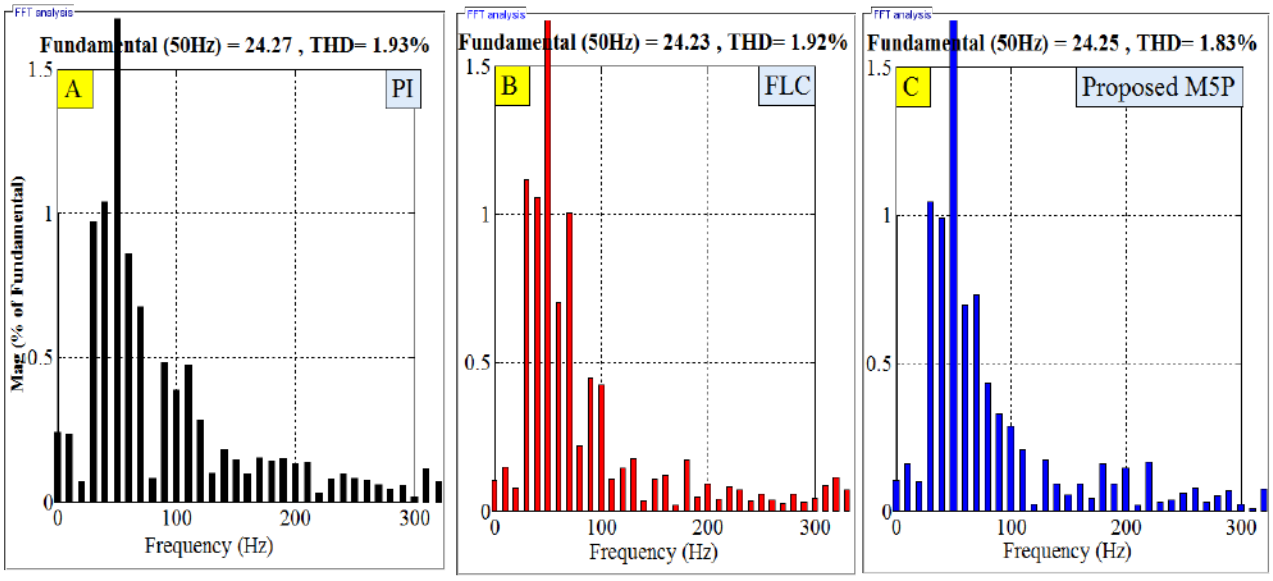


Figure 4.24: Comparative results of Total Harmonic Distortion THD

4.6 Conclusion

In this study, an advanced Maximum Power Point Tracking (MPPT) algorithm for wind turbine systems, based on a smart M5-Pruned algorithm, was proposed and tested under a realistic variable wind speed profile. The proposed strategy introduced an effective and novel form of wind power conversion characterized by fast-tracking and rapid response to atmospheric disturbances, which directly affect the output power of wind turbines and represent a significant challenge. One of the primary strengths of the M5-Pruned algorithm is its continuous adaptability, which not only overcomes the limitations of classical MPPT techniques but also maximizes the output power of wind turbines and maintains system efficiency despite wind fluctuations. Unlike other artificial intelligence systems, the proposed strategy is distinguished by its simple structure and rapid learning capability, which allows the model to be generated in a few seconds. This innovative approach offers a qualitative addition to wind energy conversion systems. Furthermore, the algorithm provides a digital program in the form of an algorithmic decision tree, enabling researchers to understand internal behaviour and smoothly address technical problems. Comparative simulation results between the proposed MPPT-M5P, MPPT-PI, and MPPT-FLC clearly demonstrated the excellent performance, effectiveness, and robustness of the control system. The integration of the proposed MPPT algorithm with wind turbine control systems will play a crucial role in advancing the widespread adoption of wind energy as a sustainable and reliable source of renewable electricity. Future studies aim to integrate this powerful M5-Pruned algorithm into solar energy systems, smart grids, signal processing systems, and remote control systems, further expanding its application and impact.

General Conclusion

This doctoral thesis has undertaken an in-depth investigation into the intelligent control of hybrid renewable energy systems—specifically the integration of wind and photovoltaic (PV) power sources into a unified, grid-connected architecture. The research was driven by the global imperative to reduce dependence on fossil fuels, mitigate greenhouse gas emissions, and meet the increasing demand for sustainable energy solutions. As renewable energy sources such as solar and wind become more economically viable and environmentally necessary, their effective integration into existing power systems poses both a challenge and an opportunity. This study addressed these concerns by proposing advanced control strategies designed to improve the stability, reliability, and efficiency of hybrid systems.

The thesis began by analyzing the limitations of traditional renewable energy systems, notably their inherent intermittency and variability. These characteristics, while manageable individually, become significantly more complex in a hybrid configuration where real-time coordination and power flow optimization are essential. To overcome these challenges, the work focused on the development and application of artificial intelligence (AI)-based control strategies—most notably, fuzzy logic controllers (FLC), artificial neural networks (ANN), and M5-Pruned decision trees. These techniques were selected for their ability to learn from data, adapt to changing environmental conditions, and provide accurate, real-time control outputs without the need for exact mathematical modeling.

A major contribution of this thesis was the design and validation of enhanced Maximum Power Point Tracking (MPPT) algorithms for both wind and solar subsystems. These intelligent MPPT methods significantly improved energy extraction under dynamic operating conditions, including rapid changes in wind speed and solar irradiance. In contrast to classical techniques such as Perturb and Observe (P&O) or Incremental Conductance (IC), the AI-based methods demonstrated superior tracking accuracy, faster convergence times, and better overall system efficiency.

Another key innovation was the implementation of a Smart Direct Power Control (DPC) strategy applied to a three-phase PWM rectifier. The DPC algorithm, integrated with neural network controllers, was shown to enhance power quality, reduce harmonics, and ensure fast dynamic response during grid disturbances. This enabled more stable interaction between the hybrid generation system and the utility grid, addressing critical concerns such as voltage regulation, reactive power compensation, and synchronization.

The thesis also explored the synergy between solar and wind resources. By modeling and simulating hybrid configurations, it was demonstrated that combining these two sources provides complementary benefits—where solar power dominates during the day

and wind energy contributes during nights or cloudy periods. This complementarity not only reduces the dependency on energy storage systems but also leads to a more balanced and reliable energy supply profile.

Beyond the technical control aspects, the research also considered the practical implications of implementing hybrid systems. Issues such as initial capital cost, system complexity, and site-specific resource availability were analyzed. It was concluded that while hybrid systems may require higher upfront investment, their long-term economic and environmental benefits—including reduced operational costs, lower emissions, and improved energy access in remote or off-grid regions—justify their adoption, especially when integrated with intelligent control strategies.

Furthermore, this thesis provides a roadmap for future advancements in hybrid renewable energy systems. Potential research directions include:

Integration of hydrogen fuel cells or other emerging storage technologies for enhanced energy autonomy.

Application of Internet of Things (IoT) and edge computing for real-time monitoring and decentralized energy management.

Development of adaptive, self-learning controllers that can further reduce dependence on predefined models.

Exploration of AI-based fault detection and predictive maintenance strategies to improve system reliability.

In conclusion, this research contributes significantly to the field of renewable energy by demonstrating how smart, AI-driven control strategies can unlock the full potential of hybrid wind-solar systems. Through rigorous theoretical modeling, simulation, and validation, it has been shown that such systems can offer a highly efficient, robust, and flexible solution for the future of sustainable energy. The methodologies proposed in this thesis lay the foundation for real-world applications that align with global environmental goals and support the transition to cleaner, smarter energy systems worldwide.

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