Universidade de Évora - Escola de Ciências e Tecnologia

Mestrado em Engenharia da Energia Solar

Dissertação

Analysis of Smart Hybrid Microgrid Systems with RE and ESS for Sustainable Grid Integration

Md Suruj Ali

Orientador(es) | Mouhaydine Tlemcani

Masud Rashel

Évora 2025

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A dissertação foi objeto de apreciação e discussão pública pelo seguinte júri nomeado pelo Diretor da Escola de Ciências e Tecnologia:

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Évora 2025

To my parents Mst. Jahanara Khatun and Md. Toslem Ali

Abstract

Analysis of Smart Hybrid Microgrid Systems with RE and ESS for Sustainable Grid Integration

This research focuses on a Smart Hybrid Microgrid System (SHMs) energy forecasting, technical design and power optimization for diverse applications, like remote areas, community based SHM's, and small commercial establishments. Integrating Renewable Energy Sources (REs), and Battery Energy Storage System (BESS) to enhance the grid integration, grid stability, and reliability. This study begins with an in-depth literature review, investigate existing Smart Hybrid Microgrid System (SHMs) energy forecasting, modeling, optimization, along with their challenges and advantages. The Long short-term memory (LSTM) machine learning model is employed for energy demand forecasting, and renewable energy generation forecasting. MATLAB/Simulink is used for SHM system modeling, and optimization of renewable power generation through Maximum Power Point Tracking (MPPT) algorithms, enabling performance analysis for proposed electrification grid network. The major components of the SHM's include solar photovoltaic panels, wind turbines, battery energy storage system, peripheral power electronics, and measurement blocks. The machine learning and MATLAB/Simulink models demonstrate accuracy, efficiency, convergence time, and power losses minimization. The smart hybrid microgrid system optimized using traditional and advanced MPPT algorithms, such as Perturbation and Observation (P&O), Predictive Control Method (PCM), Fuzzy Logic, and Artificial Neural Network (ANN). The result shows that the forecasting model achieves 98% accuracy, while ANN MPPT algorithm provides the highest efficiency with 99.6%, compared to the other MPPT algorithms. The key finding provides comprehensive insights into demand and generation forecasting, power optimization, and SMH's technical analysis, ensure reliability and sustainability. The research concludes with recommendations for future improvements, financial assessment, implementation strategies, real time energy management, and monitoring which contribute more cleaner and resilience energy future.

Keywords: Hybrid Microgrid System, Energy Forecasting, Optimization, LSTM, MPPT Algorithms, Grid Integration, MATLAB/Simulink

Resumo

Análise de sistemas de micro-redes híbridas inteligentes com RE e ESS para integração de redes sustentáveis

Esta investigação centra-se na previsão energética, na conceção técnica e na otimização da potência de um sistema de microrredes híbridas inteligentes (Smart Hybrid Microgrid SHM) para diversas aplicações, tais como áreas remotas, SHM de base comunitária e pequenos estabelecimentos comerciais. Integração de fontes de energia renováveis (Renewable Energy Sources ER) e de sistemas de armazenamento de energia em baterias (Battery Energy Storage System BESS) para melhorar a integração, a estabilidade e a fiabilidade da rede. Este estudo começa com uma revisão aprofundada da literatura, investiga a previsão de energia, modelação, otimização do Sistema Híbrido Inteligente de Microrredes (SHMs) existente, juntamente com os seus desafios e vantagens. O modelo de aprendizagem automática de memória de curto prazo longa (Long short-term memory LSTM) é empregue para a previsão da procura de energia e para a previsão da produção de energia renovável. O MATLAB/Simulink é utilizado para a modelação do sistema SHM e para a otimização da produção de energia renovável através de algoritmos de seguimento do ponto de potência máxima (MPPT), permitindo a análise do desempenho da rede de eletrificação proposta. Os principais componentes dos SHM incluem painéis solares fotovoltaicos, turbinas eólicas, sistema de armazenamento de energia em baterias, eletrónica de potência periférica e blocos de medição. Os modelos de aprendizagem automática e MATLAB/Simulink demonstram precisão, eficiência, tempo de convergência e minimização de perdas de energia. O sistema de microrrede híbrida inteligente foi optimizado utilizando algoritmos MPPT tradicionais e avançados, tais como Perturbação e Observação (P&O), Método de Controlo Preditivo (PCM), Lógica Difusa e Rede Neuronal Artificial (RNA). O resultado mostra que o modelo de previsão atinge 98% de exatidão, enquanto o algoritmo ANN MPPT proporciona a maior eficiência com 99,6%, em comparação com os outros algoritmos MPPT. A principal conclusão fornece uma visão abrangente sobre a previsão da procura e da produção, a otimização da energia e a análise técnica da SMH, garantindo a fiabilidade e a sustentabilidade. A investigação conclui com recomendações para melhorias futuras, avaliação financeira, estratégias de implementação, gestão de energia em tempo real e monitorização que contribuem para um futuro energético mais limpo e resiliente.

Palavras-chave: Microrede Híbrida Inteligente, Previsão de Energia, Otimização, LSTM, Algoritmos MPPT, Integração à Rede, MATLAB/Simulink.

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Nomenclature and Abbreviations

CO_2	Carbon Dioxide [ppm]
Eg	Energy Gap [eV]
Ec	Conduction Band [-]
Ev	Valence Band [-]
E_G	Bang GAP Energy [eV]
m	Ideality Factor
n_i	Intrinsic Semiconductor
K_B	Boltzmann constant [JK^{-1}]
EF	Fermy energy [eV]
h	Planck´s constant [J.s]
Vt	Thermal voltage [V]
Is	Saturation current [A]
Iph	Photo Current [A]
Iph,ref	Referred photo current [A]
T	Temperature [°C]
Tamb	Ambient temperature [°C]
T_{ref}	Reference Temperature
Rs	Series Resistance [Ω]
Isc	Short circuit current [A]
Voc	Open circuit voltage [V]
Impp	Current at maximum point [A]
Rsh	Shunt Resistance [Ω]
Vmpp	Voltage at maximum point [V]
Pmpp	Maximum Power Point [W]
Ki	Temperature coefficient [A/°C]
Tnom	Nominal temperature [°C]
I_L	Photocurrent [A]
I_d	Diode Current [A]
D	Diode
R_{sh}	Shunt Resistor [Ω]
I	Current [A]
V	Voltage [V]
G	Irradiance [W/m^2]
G_{ref}	Reference Irradiance [W/m^2]
I_0	Saturation current [A]
q	Elementary charge [C]
P_{in}	Input Power [W]
P_{out}	Output Power [W]
A	Solar Cell Area [m^2]

T_{cell}	Cell Temperature [°C]
R_L	Load Resistor [Ω]
I_{pv}	Photovoltaic Current [A]
V_{pv}	Photovoltaic Voltage [V]
V_s	Input Voltage [V]
V_o	Output Voltage [V]
V_L	Load Voltage [V]
L	Inductor [henry (H)]
V_{ref}	Reference Voltage [V]
β	Temperature Coefficient [-%/°C]
v	Wind Velocity [m/s]
RE	Renewable Energy
SHMs	Smart Hybrid Microgrid System
REs	Renewable Energy Sources
BESS	Battery Energy Storage System
LSTM	Long Short-Term Memory
MPPT	Maximum Power Point Tracking
P&O	Perturbation and Observation
PCM	Predictive Control Method
ANN	Artificial Neural Network
FLC	Fuzzy Logic Control
FSCC	Fractional Short Circuit Current
FOCV	Fractional Open Circuit Voltage
PSO	Particle Swarm Optimization
GA	Genetic Algorithm
ANFIS	Adaptive Neuro-Fuzzy Inference System
ModP&O	Modified Perturbation and Observation
AGM	Adaptive Gradient Method
ACO	Ant Colony Optimization
FSM	Fast-Sweep Method
DPM	Dual-Perturbation Method
VSSIncCond	Variable Step Size Incremental Conductance
PCC	Point of Common Coupling
DC	Direct Current
AC	Alternating Current
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
R^2	Coefficient of Determination
NOCT	Nominal Operating Cell Temperature
FF	Fill Factor
PV	Photovoltaic
WT	Wind Turbine
MPP	Maximum Power Point

NREL	National Renewable Energy Laboratory
STC	Standard Testing Condition
IGBT	Insulated Gate Bipolar Transistors
ML	Machine Learning
ARIMA	Autoregressive Integrated Moving Average
SARIMA	Seasonal Auto-Regressive Integrated Moving Average
RNN	Recurrent Neural Network
IEA	Internation Energy Agency
PVGIS	Photovoltaic Geographical Information System
IQR	Interquartile Range

Chapter 1

Introduction

1.1 Background

Recently the global energy landscape is shifting to renewable energy systems, which are driven by climate mitigation, increase energy security, and bridge the electrification gap underprivileged areas. Conventional centralized grid systems often suffer from power disruption, grid instability, high power transmission losses, and dependency on fossil fuels. To address those challenges, a decentralized system, like smart hybrid microgrid system (SHMs) provides a reliable and sustainable energy solution [1]. These systems incorporate with Renewable energies sources (REs), like Solar photovoltaic (PV) panels, Wind turbines (WT), and Battery energy storage system (BESS) that offer reliable and stable energy supply through the grid network. These SMHs are particularly essential for remote regions, community based, and small commercial applications where grid stability and reliability are crucial [2]. The design of such SHMs requires several challenges, such as renewable energy resource feasibility, intermittency, power optimization, grid stability and reliability [3].

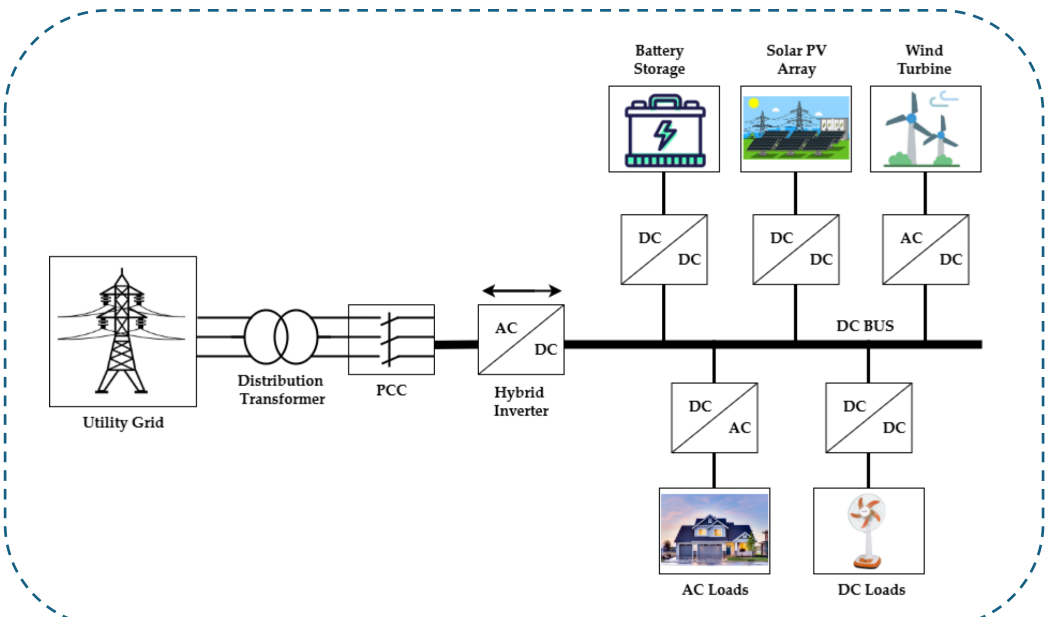

Figure 1.1: Smart hybrid microgrid system schematic diagram

A smart hybrid microgrid system integrated with several renewable energy resources, AC and DC loads, hybrid grid tied inverter, string inverters, controlling units and distribution transformers.

1.2 Motivation

According to world energy poverty data [4], 1.18 billion people can not use electricity for several reasons. One of the reasons is the unavailable grid infrastructure in remote areas or small community areas. The motivation behind this study is to promote clean renewable energy solutions using decentralized hybrid microgrid infrastructure. There is a deficiency of robust energy access in underprivileged areas due to the intermittent nature of renewable energy. Where smart hybrid microgrid system (SHMs) plays a crucial role to serve continuous energy supply. The traditional hybrid microgrid system often fails, due to lack of feasibility study (energy demand, and renewable energy generation forecasting), grid stability and reliability assessment. By leveraging modern technologies like machine learning models, and sophisticated power optimization algorithms promise to bridge the gaps. Using those artificial models and power optimization algorithm, hybrid microgrid system can minimize demand-supply mismatch, improve grid stability, grid integration, and mitigate carbon footprints.

1.3 Literature Review

The adaptation of global electricity is rapidly changing towards renewable energy. Solar photovoltaic (PV) and wind energy are the leading renewable energy sources. According to Ember data, solar and wind technology cumulatively generate approximate 13.4% global energy by 2023 [5], that is contributes more than 70% of renewable energy globally among all renewable energy resources. The energy landscape suggests that in 2030 combinedly renewable contribution will be 46% of global electricity [6]. To use renewable energy, there are some drawbacks due to intermittency nature. Hence renewable energy sources (REs) integration with the grid also increases, which led to grid stability failure [7]. If renewable energy integration rapidly increases and does not maintain the grid code, it can be major voltage fluctuation in PCC. Increasing renewable energy significantly raise the concern about energy reliability. To overcome those issues, hybrid microgrid is one of the best solutions. This literature review focuses on advancements in smart hybrid microgrid system (SHMs) [8], integration into renewable energy resources [9], machine learning language for energy demand and renewable energy resource forecasting [10], and energy optimization using maximum power point tracking (MPPT) algorithms [11]. One of the characteristics is that a smart hybrid microgrid system has the ability to operate independently or integrate with nation grid, which makes SHMs more reliable and sustainable energy solutions. Integrate renewable energy sources, like solar photovoltaic panels, wind turbines, battery energy storage system (BESS) presents both opportunities and challenges [11]. Accurate energy demand and renewable energy resource forecasting is crucial to enhance hybrid microgrid optimization, energy management and operation. Traditional forecasting models are not efficient to capture complex energy patterns data. The advance artificial machine learning models has revolutionized energy demand and REs forecasting by the utilization of large datasets that identify complex patterns and trends [11-17]. In this research, Long Short-Term Memory (LSTM) machine learning model has been employed to forecast the proposed location of energy demand and available renewable energy resources. There are several forecasting methods available, but LSTM and ANN models are the most used machine learning models for energy forecasting [18]. Maximum Power Point Tracking (MPPT) is crucial to extract maximum power from solar PV panels and wind power under extreme weather conditions. It operates continuously by tracking and adjusting the operating point of the solar PV system to make sure that this point follows it's I-V (current-voltage) curve where MPP power is generated. There are several MPPT methods that have been published in the literature to achieve optimal performance. The most used MPPT algorithms of direct methods are Perturb and Observe (P&O), and Incremental Conductance. Although there are some prominent MPPT methods such as indirect methods Fractional Short Circuit Current (FSCC) and Fractional Open Circuit Voltage (FOCV) and soft computational methods, Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Fuzzy Logic Control (FLC), Artificial Neural Network (ANN), Model Predictive Control (MPC), Adaptive Neuro-Fuzzy Inference System (ANFIS), Modified P&O (ModP&O), Adaptive Gradient Method (AGM), Ant Colony Optimization (ACO), Fast-Sweep Method (FSM), Dual-Perturbation Method (DPM), and Variable Step Size Incremental Conductance (VSSIncCond) [34-43]. Recent research demonstrates that machine learning model based MPPT techniques performance are fer better than traditional MPPT algorithms. For this research four (4) different MPPT algorithms (P&O, Predictive Control Method, Fuzzy Logic and Artificial Neural Network) are used to identify the best MPPT model for smart hybrid microgrid (PV) system power optimization. Including machine learning model (LSTM), and power optimization MPPT algorithm (ANN based MPPT) are incorporate into smart hybrid microgrid system (SHMs) MATLAB/Simulink modeling goals to enhance renewable energy resources forecasting accuracy and maximize power extraction from solar PV panels, which improve overall efficiency, reliability and the SHMs operation.

1.4 Research Objectives

This research represents the following objectives:

1. To develop a Long Short-Term Memory (LSTM) machine learning model for accurate energy demand forecasting and renewable energy resources forecasting.
2. Evaluate the performance of different Maximum Power Point Tracking (MPPT) algorithms such as P&O, Predictive Control Method (PCM), Fuzzy Logic and ANN to maximize solar PV panels power output.
3. Design and simulate a Smart Hybrid Microgrid System (SHMs) architecture in a MATLAB/Simulink environment with best fitted MPPT algorithm.

4. Perform MATLAB/Simulink models simulation for MPPT (PV) and SHMs performance analysis, towards efficiency, convergence time, power losses, grid stability, and reliability.
5. Provide essential recommendations for smart hybrid microgrid system deployments, optimization, real time monitoring, and resiliency enhancements.

1.5 Dissertation Organization

The dissertation is organized into six (6) chapters:

Chapter 1 (Introduction):

This chapter illustrating the problems background, motivation led to do the research, research objectives, and the importance of this study. It highlighted global energy transition, and the significance decentralized smart hybrid microgrid system for sustainable and reliable energy solutions.

Chapter 2 (Basic Principles and Technologies (PV)):

This chapter represents an overview of solar PV cells modeling, irradiance and temperature effect on solar PV. It provides fundamental principles of DC-DC power conversion technologies, and MPPT algorithms for optimize power generation.

Chapter 3 (RE Resource and Demand Forecasting):

This chapter provides an overview for renewable energy resource forecasting and energy demand utilizing advanced machine learning language (LSTM). It comprises with data collection and processing, model training, testing and validation. Performance metrics assessment (MAE, RMSE, R^2) for precise forecasting.

Chapter 4 (Smart Hybrid Microgrid System Modelling and Design):

This chapter focuses on modeling and designing for proposed Smart Hybrid Microgrid System (SHMs) in the MATLAB/Simulink environment. It included mathematical modeling of smart hybrid microgrid components, and different types of hybrids microgrid architectures.

Chapter 5 (Results and Discussion):

This chapter represents machine learning model (LSTM) results and accuracy and performance metrics with discussions, and comparative analysis of multiple MPPT (PV) algorithms for power optimization. Also proposed Smart hybrid microgrid system efficiency, grid stability, and power losses analysis.

Chapter 6 (Conclusion):

In this chapter summarizes the main findings of the study and provides necessary recommendations for future research, including real time monitoring, scalability, policy, economic viability.

Chapter 2

Basic Principles and Technologies (PV)

2.1 Overview of Solar PV Energy

As the worldwide demand of sustainable and clean renewable energy rises, the energy sources like solar, wind, geothermal, ocean and hydro energy have taken center place. Among all of these, solar energy has the potential to meet the energy demand from small scale to large scale. Still, the solar energy contribution is less than 3.6% towards global energy production [19]. Solar panels capture the sunlight and converts into electricity. It can reduce the toxic gases like carbon (CO2) emission and dependency on traditional fossil fuels-based plant which significantly mitigate climate change.

2.2 Brief History of Solar PV Technology

In 1839 French physicist Alexandre Edmond Becquerel first observe photovoltaic effect. He proves that the metallic plates such as silver or platinum when immersed in an electrolyte have potential to generate small electrical voltage when exposed to light. This finding was groundwork to develop a solar photovoltaic panel. In 1877, two scientists from North America, W.G Adams and R.E. Day first used solid-state device which converts sunlight into electricity using selenium that has photoconductive properties.

Figure 2.1 Modern solar cell inventors from Bell Labs [20].

They used layer of selenium film deposited with iron substrate; semitransparent thin gold film that is serve frontal contact. The energy conversion efficiency was 0.5%. In 1905, the most popular scientist sir Albert Einstein explains the photovoltaic effect mechanism. After that in 1921, he received the Nobel Prize in Physic. The modern technology of silicon based solar PV was first created at Bell Laboratories in 1954. Over the years solar PV technology has increased efficiency and durability. Moreover, the prices, affordability and scalability lead to their widespread adaption. Today, solar PV panels are the most common renewable energy source to generate clean energy.

2.3 Importance of Solar PV in Renewable Energy

Solar PV technology is one of the promising renewable energy sources which is game changer towards worldwide energy transition. It is reducing conventional fossil fuels-based power plants and greenhouse gases. Now a days, solar PV panels are cheaper renewable energy solution compared to others renewable energy sources. Due to environmentally friendly technology, it does not pollute environment such as air, water, and soil. It also mitigates global warming, which makes it one of the best options for clean energy production. Sunlight is abundant for that reason; solar PV energy is reliable and cost effective. Once solar panels installation serves more than 20 years of green energy. Whether conventional fossil fuel-based energy is costly and its continuously raises the price, also it is the reason for producing toxic greenhouse gases and global warming. Solar PV panels offer energy independence, because they do not rely on electrical grids and provide reliable energy in outage situations. From small individual rooftops to large scale solar power plants has the capability to meet the energy demands. This flexibility enables decentralized energy generation and replaces conventional centralized grid systems. In remote areas, where conventional grid infrastructure is not available, a small solar plant can bring light and serve energy to empowering communities which significantly improve quality of life.

Figure 2.2 Solar minigrid empowering community [21]

Solar PV will be more economically attractive energy solution due to continuous research of technological advancement. This affordability also reduces energy storage costs, which accelerates solar energy adaptation globally and pushes the clean and sustainable energy growth.

2.4 Basic Principles of Solar Photovoltaic Technology

2.4.1 Solar Photovoltaic Effect

Photovoltaic effect refers to the process, which generates voltage and current when it is exposed to light. Due to this fundamental effect solar cells covert, the light to electrical energy [21]. This photovoltaic effect has a close relation with photoelectric effect. For both of these phenomena light is absorbed, which excite an electron to a large energy state. When photons of sunlight strike to surface of solar cells, it transfers energy to electrons within semiconductor materials. This energy allows electrons to release their atoms and create free electron (current) flows. The most recognized application for photovoltaic effect is used in solid-state devices especially in photodiodes. When sunlight or any other high energy light incidents into the photodiode, the electrons of valance band absorb that energy. As a result, they become excited and jump into conduction band to be free.

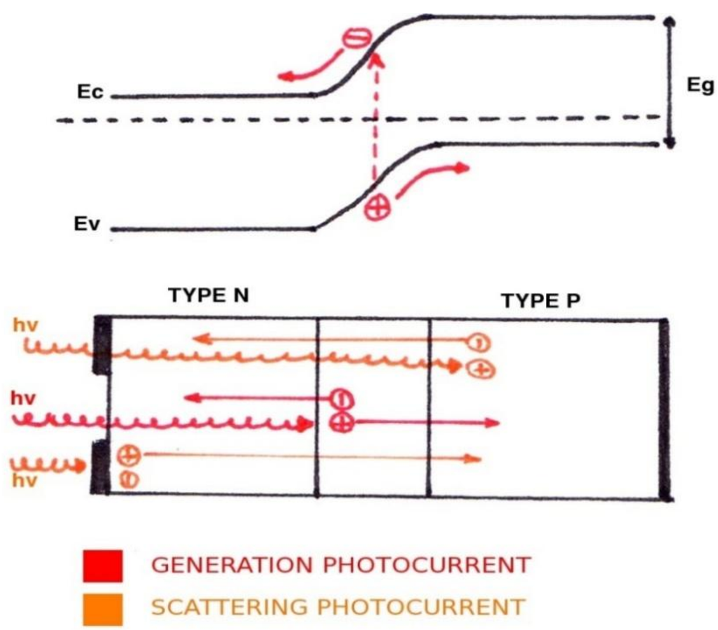

Figure 2.3 photovoltaic effect bang diagram [22]

From those all-excited electrons being diffused, and some of them reach to rectify junction (P-N junction diode). Because of free movement, this electron passes through material where they build in potential which is known as "Galvani potential", that accelerate electrons to n-type semiconductor and generate electromotive force to produce electrical current. This process converts sunlight energy into electrical energy [23]. The photon is defined by its energy (E) and wavelength (λ). The mathematical relationship between them is given by:

$$E = hc/\lambda \tag{2.1}$$

Where,

$h = Planck's\ constan$ [J.s]

$c = Speed\ of\ the\ light$ [m/s]

$\lambda = Photon\ wavelength$ [m]

$E = Photon\ energy$ [J]

To generate the current, photon energy should be higher than the bandgap of material.

All the photovoltaic effects occur in solid material involve with several things.

- Light must have to be absorbed by solid materials
- Free charge carrier produces through absorption
- An internal variation or nonuniform distribution impurities or faults are the reason to develop internal electric fields which separate two types of charge carrier.
- Electrical connections

The diagram represents photovoltaic effect is given below.

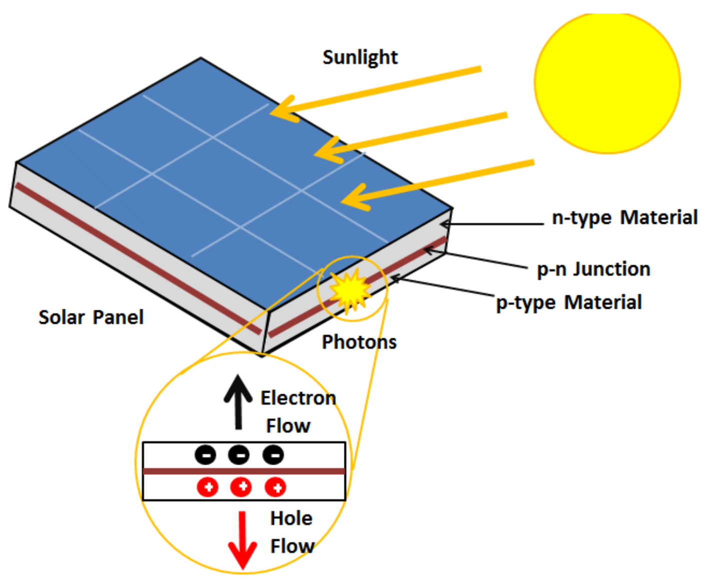

Figure 2.4 Photovoltaic effect diagram [23]

However, this photovoltaic effect will occur when two photons are simultaneously absorbed. This phenomenon is called "two photons photovoltaic effect". The photovoltaic effect will continue as long as sunlight incidents to solar cells. To extract the current for electrical circuits, it must have to be an electrical field which accelerates the electrons to a particular direction.

2.4.2 Basic Working Principle of a Solar Cell

The solar cell is a solid-state electronic device that has capabilities to convert sunlight into electricity. When sunlight is shining and falls into solar cells, it produces power which is the product of voltage and current. The electrical characteristics (voltage, current and resistance) will change with changing light. To complete this process semiconductor material is needed. Solar cell structure basically is an absorption layer with positive (+) and negative (-) terminal as like battery electrode connected. To make one directional electron flow through an electromagnetic force, an internal electric field is necessary to produce practical p-n junction. The material of p-type semiconductors that conduct huge number of holes and n-type semiconductors can conduct huge number of electrons rather than holes.

The main requirement to produce photovoltaic energy is electronic asymmetric structure between p-type and n-type semiconductors. Figure 2.6 shows a band diagram of a solar cell structure.

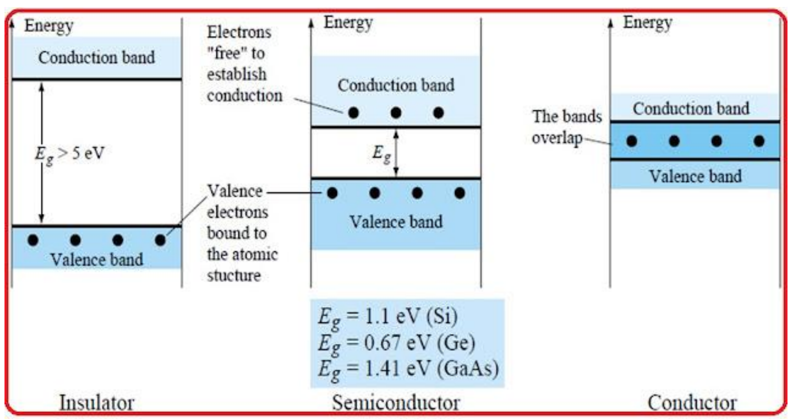

Figure 2.5: Solar cell band diagram [24]

When sunlight strikes the n-type region and penetrate into depletion region, the photon energy is enough to create electron-hole pairs within depletion region. The electric field present in this depletion region drives the electrons from there. Hence the concentration of holes in p-type region and electrons of n-type region become high, it is known as potential difference (voltage) if load is connected [25].

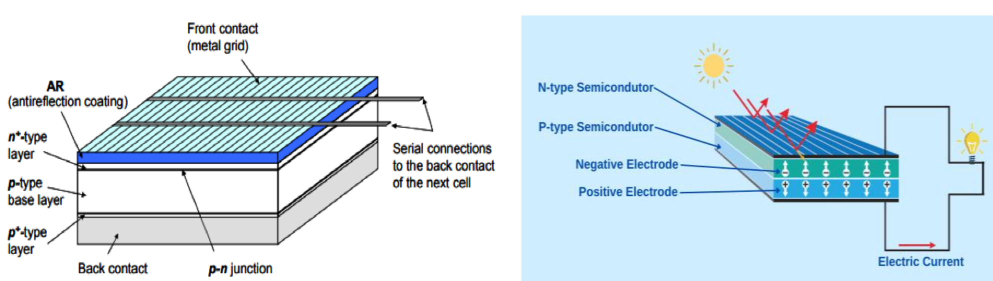

Figure 2.6: Solar cell structure diagram [26]

This is the reason electron flow through external electrical load and produce direct current (DC). This process gives the permission to get steady DC power, which we can use in daily life.

2.4.3 Modeling of Solar PV Cells

Solar PV cells modeling involves a mathematical representation which can simulate equivalent electrical circuit behavior under any environmental conditions. A photovoltaic solar panel consists of several cells. There are several models of equivalent circuit such as single diode model, double diode model and three diode model [25]. From those, single diode model is most commonly used, that represents an equivalent circuit consisting of a current source, a diode, a resistor (Rs), and shunt resistor (R_{sh}) component (figure 2.8). The symbol of current source illustrates photocurrent generator that from sunlight and diode represent p-n junction characteristic within solar cells. The series resistance (Rs) accounts internal losses and parallel or shunt resistance (R_{sh}) that is for leakage current. All those elements make the effect of overall performance and efficiency of solar photovoltaic cells.

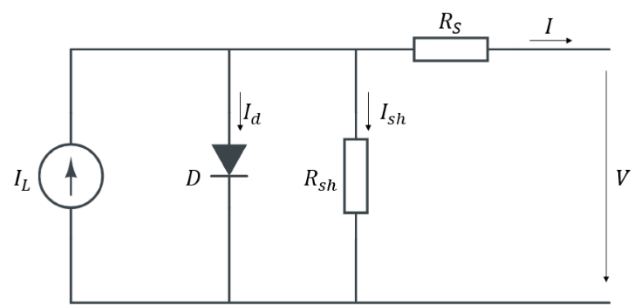

Figure 2.7: Equivalent circuit of solar cell

Where,

$I_L = Photocurrent\ [A]$
$I_d = Diode\ current$ [A]
$D = Diode$
$I_{sh} = Parallel\ or\ shunt\ current$ [A]
$R_{sh} = Parallel\ or\ shunt\ resistance$ [Ω]
$R_s = Series\ current$ [Ω]
$I = Solar\ cell\ current$ [A]
$V = Solar\ cell\ voltage$ [V]

The single diode solar cell model is specifically effective for predicting I-V curve, where the main electrical parameters are open circuit voltage (Voc), short circuit current (Isc) and maximum power point (MPP) [13]. This model helps the researchers and engineers to design a highly efficient solar cells and improve their performance under diverse conditions such as irradiance and temperature variation.

- **Key Parameters for Solar PV Cell Model**

Before exploring different types of solar cell modeling, it is important to first explore the significance of solar cell parameters which define the efficiency and performance. To understand all those parameters is crucial, because those are influenced by environmental factors such as irradiance and temperature. It can change the solar PV cell operating conditions (MPP).

- **Photocurrent of Solar PV Cell ($\mathbf{I_L}$)**

The photocurrent (I_L) illustrates the current that is generated by solar PV cell when it is exposed to sunlight. The photocurrent generally depends on standard temperature, irradiance, and their changes, also the changes of temperature coefficient. As irradiance increases, temperature also increases while photocurrent will be decrease [28]. The mathematical expression is:

$$I_L = (I_{sc} + k.(T - T_{ref})).\frac{G}{G_{ref}} \tag{2.2}$$

Where,

$I_L = Photocurrent\ [A]$
$I_{sc} = Short\ circuit\ current$ [A]
$k = Temperature\ coefficient\ for\ current\ [\frac{A}{K}]$
$T = Solar\ PV\ cell\ temperature$ [K]
$T_{ref} = Reference\ temperature$ [K]
$G = Irradiance$ [W/m²]
$G_{ref} = Reference\ irradiance$ [W/m²]

- **Diode Saturation Current of Solar PV Cell ($\mathbf{I_0}$)**

Diode saturation current is the main factor that influences the open circuit voltage (Voc). This parameter reflects the leakage current, when no sunlight is available. As temperature increases, the diode saturation current also increases exponentially because of electrons recombination and holes among p-n junction (figure 2.9).

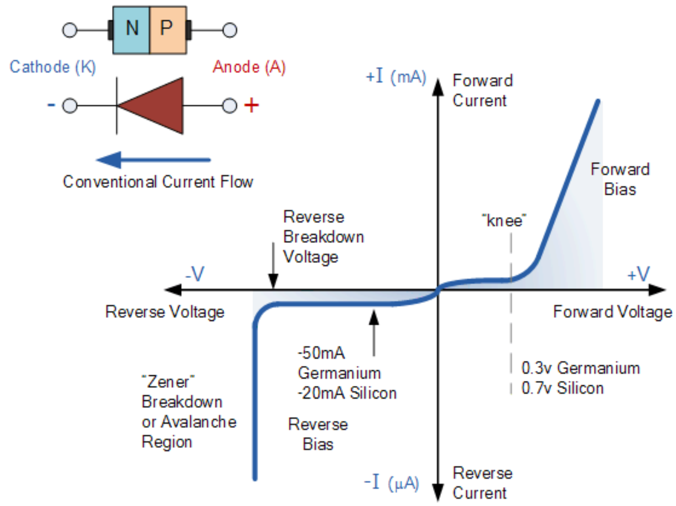

Figure 2.8: Diode saturation current graph [29].

The mathematical expression for diode saturation current is:

$$I_0 = I_{0,ref} \cdot \left(\frac{T}{T_{ref}}\right)^3 . \, exp\left[\frac{q.E_g}{K_B}\left(\frac{1}{T_{ref}} - \frac{1}{T}\right)\right] \tag{2.3}$$

Where,

$I_0 = Diode\ saturation\ current\ [A]$

$I_{0,ref} = Saturation\ current\ of\ reference\ temperature$ [A]

$T = Solar\ PV\ cell\ temperature\ [K]$

$T_{ref} = Reference\ temperature\ [K]$

$q = Elementary\ charge$ [C]

$E_g = Semiconductor\ bandgap\ energy$ [eV]

$K_B = Boltzmann\ constant$ [J/K]

- **Series Resistance of Solar PV Cell ($\mathbf{R_s}$)**

The resistance refers to resistive losses on solar cell along with semiconductor contacts, materials and interconnections (figure 2.10). It can be determined experimentally by the slope of I-V curve that is closer to open circuit voltage (Voc).

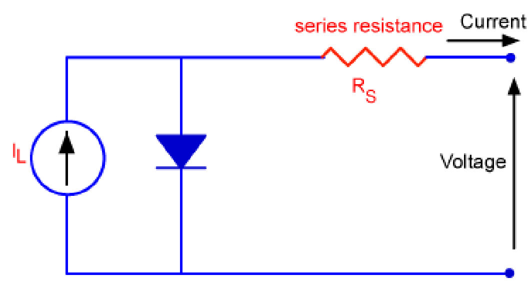

Figure 2.9: Series resistance diagram of solar cell

According to the study [30], there is a dependency on changes of irradiance and temperature for series resistance (Rs) across the conditions, hence it can be express as the equation:

$$R_s < \frac{0.1\,V_{oc}}{I_{sc}} \tag{2.4}$$

$$R_s = R_{s,ref} \tag{2.5}$$

The equation (5) refers to series resistance (R_s) is equal the reference resistance ($R_{s,ref}$).

- **Open Circuit Voltage of Solar PV Cell ($\mathbf{V_{oc}}$)**

It is the maximum voltage that solar cell can produce, when zero current flow. The open circuit voltage (Voc) is determined by the properties of solar cell material and make balance within saturation current and photocurrent [31], figure 2.11.

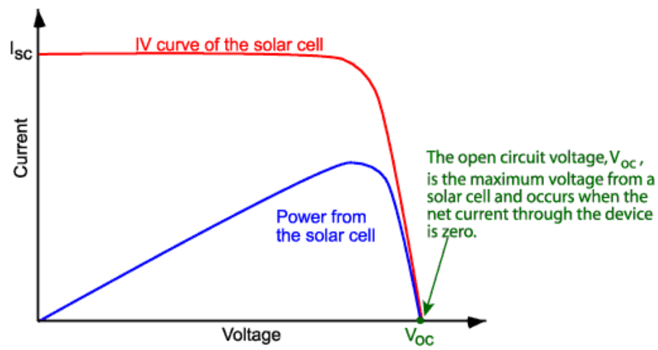

Figure 2.10: Solar cell I-V curve with open circuit voltage

The mathematical expression for open circuit voltage (Voc) found by,

$$V_{oc} = \frac{nK_BT}{q}.\,ln\left(\frac{I_L}{I_0} + 1\right) \tag{2.6}$$

Where,

$V_{0c} = Open\ circuit\ voltage\ [V]$
$I_L = Photocurrent$ [A]
$T = Solar\ PV\ cell\ temperature\ [K]$
$I_0 = Saturation\ current\ of\ diode\ [A]$
$q = Elementary\ charge$ [C]
$n = Ideality\ factor$
$K_B = Boltzmann\ constant$ [J/K]

While net current is zero the equation (8), indicate open circuit voltage (Voc) rise linearly with the temperature. It also depends on the photo generated (I_L) current and saturation current (I_0).

- **Short Circuit Current of Solar PV Cell (I_{sh})**

This current is the maximum current, when solar PV cells are shorted. Short circuit refers to when there is no voltage [31]. Which indicates solar PV cells can produce maximum current in ideal conditions (figure 2.12).

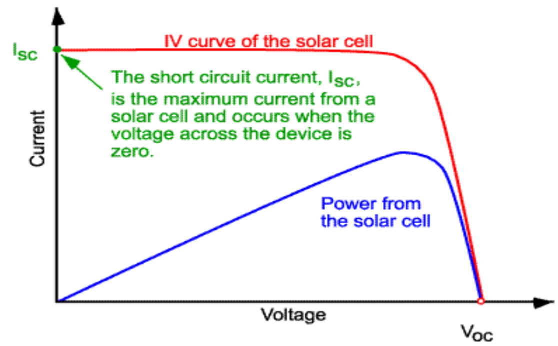

Figure 2.11: Solar cell I-V curve with short circuit current (Ish)

The mathematical expression of short circuit current is:

$$I_{sh} \approx I_L \tag{2.7}$$

Where,

$I_{sh} = Short\ circuit\ current$ [A]

$I_L = Photocurrent$ [A]

- **Maximum Power Point of Solar PV Cell (MPP)**

The parameter of MPP is crucial to optimize the solar energy generation and enhance performance towards practical applications. It is the point of I-V curve, where product of voltage and current is maximum, which represents solar PV cell maximum power (figure 2.13). The MPP voltage drift may depend on diverse factors such as irradiance, temperature and degradation of device [32].

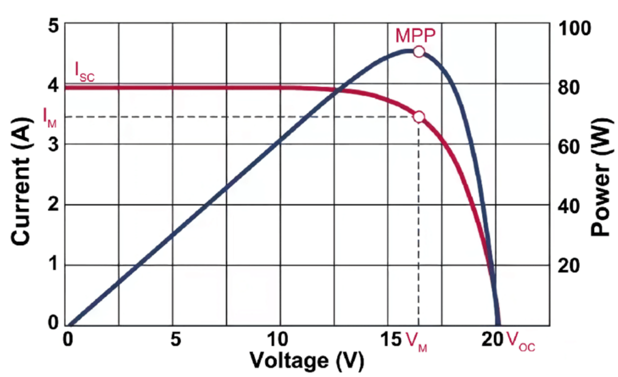

Figure 2.12: Solar PV cell maximum power point (MPP) curve [32]

The mathematical expression for MPP of solar PV cell is:

$$P_{max} = V_{mpp} \times I_{mpp} \tag{2.8}$$

Where,

$P_{max} = Maximum\ power\ point$ [W]
$V_{mpp} = Voltage\ at\ MPP$ [V]
$I_{mpp} = Current\ at\ MPP$ [A]

- **Ideality Factor of Solar PV Cell (n)**

It is an essential parameter for the diode that expresses the behavior of solar cells p-n junction and different semiconductors devices. It quantifies the ideal behavior of perfect diode. In practical solar cells, ideality factor values between 1 and 2 (figure 2.14), which varies in accordance with their characteristics [33].

- n = 1: Represents the ideal behavior, due to recombination occurs on depletion region.
- n > 1: Represents non ideal behavior, due to material defects or surface recombination

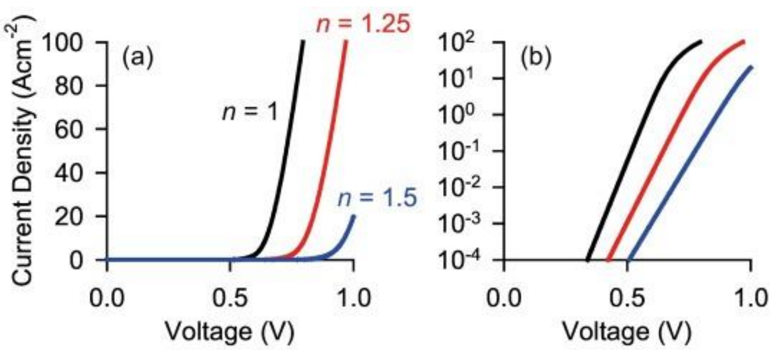

Figure 2.13: Ideality factor of SiC Schottky diode [33]

According to the equation (8), ideality factor can influence solar cells I-V curve that has direct impact on open circuit voltage (Voc) and overall efficiency.

- **Maximum Efficiency of Solar PV Cell (η)**

It refers to maximum possible light conversion into electrical energy within extreme environmental conditions (figure 2.15). A solar cell efficiency is influences by many factors, such as properties of material, cell design, intrinsic physical limitation, and variable weather conditions [34].

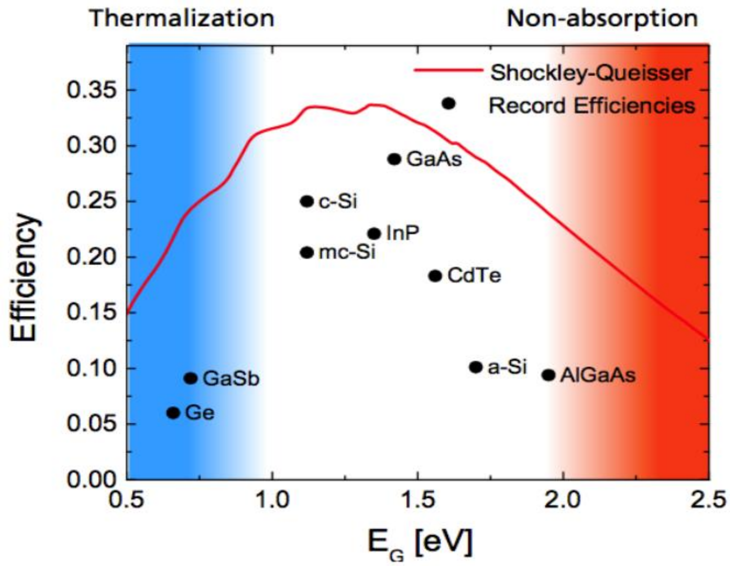

Figure 2.14: Maximum efficiency of different material based solar cell [34]

The mathematical expression of maximum efficiency is:

$$\eta = \frac{P_{out}}{P_{in}} = \frac{V_{mp} \cdot I_{mp}}{G \cdot A} \tag{2.9}$$

Where,

$V_{mp} = Maximum\ power\ point\ voltage\ [V]$

$I_{mp} = Maximum\ power\ point\ current\ [I]$

$G = Solar\ irradiance$ [W/m^2]

$A = Solar\ cell\ area$ [m^2]

According to theory, the single junction silicon based solar cell has the maximum efficiency around 33. 7%, while commercial silicon based solar cell efficiency within 15% to 22%. However, multijunction cells achieve more than 40% efficiency. In figure 2.16, it shows a recent research chart of solar cells efficiency [35].

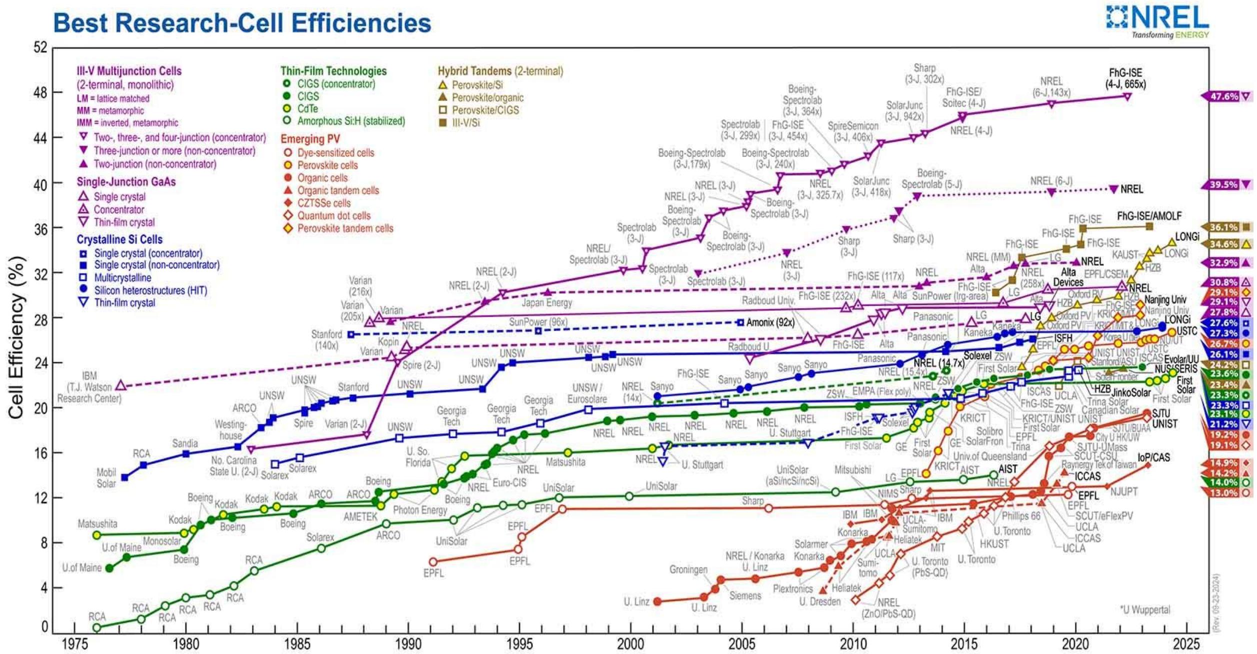

Figure 2.15: Recent research chart of solar cells (NREL) [35]

- **Fill Factor of Solar PV Cell (FF)**

The fill factor is one of the major parameters that identifies the efficiency of solar cells and modules. It is the ratio of maximum output power and the theorical output power of the solar cells. The fill factor specifies the solar cell performance compared to theorical limits. It is easy to identify solar cells performance and losses considering FF values. High Fill Factor (FF) means the power losses are low, it is caused by internal resistance of solar cells, for instance series (R_s), and shunt (R_{sh}) resistance [36].

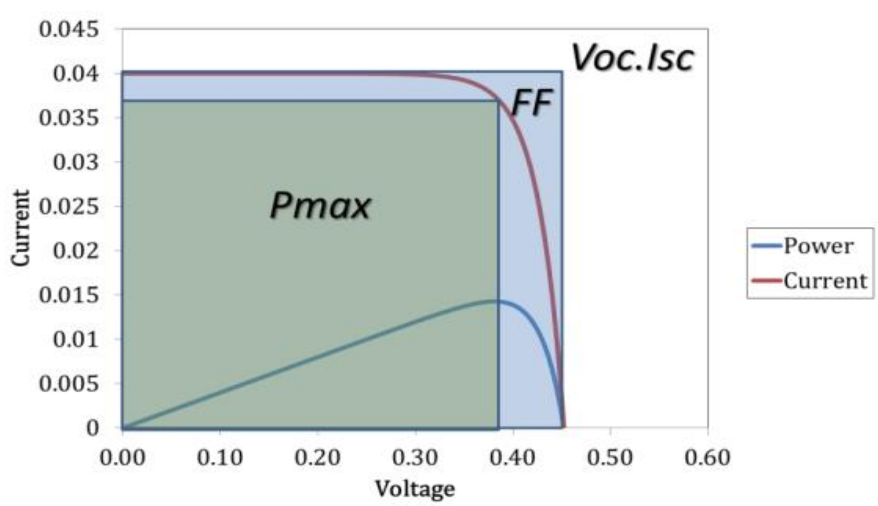

Figure 2.16: Solar cell fill factor graph [36]

The mathematical expression of fill factor is:

$$FF = \frac{P_{mp}}{V_{oc} \times I_{sc}} = \frac{V_{mp} \cdot I_{mp}}{V_{oc} \cdot I_{sc}} \tag{2.10}$$

Where,

$FF = Fill\ factor$
$V_{mp} = Maximum\ power\ point\ voltage\ [V]$
$I_{mp} = Maximum\ power\ point\ current\ [A]$
$V_{oc} = Open\ circuit\ voltage$[V]
$I_{sc} = Short\ circuit\ current$ [A]

Usually, a commercially well-known solar cell fill factor values are between 0.7 to 0.85 and ideal solar cell value is near to 1. It is basically dependent on materials and solar cell design. If the FF value is low, it indicates internal resistivity high- or low-quality materials which reduces solar cell efficiency to convert light into electricity.

- **Cell Temperature (T_{cell})**

Solar cell temperature is crucial; it directly affects efficiency and performance. As irradiance is increased simultaneously, the temperature also increases. This high temperature impacts the solar cell and reduces efficiency due to electrical characteristics. Each of the solar cell's materials has particular temperature coefficient which indicates performance degradation while raising the temperature. For standard quality silicon has the temperature coefficient between -0.4%/°C to -0.5%/ °C of power. This means each of degree Celsius temperature increases over STC (25°C) limit, it will reduce -0.4%/°C to -0.5%/ °C of efficiency. The cell temperature relies on diverse environmental factors, for instance solar irradiance, ambient temperature and wind speed [37].

The mathematical expression of solar cell temperature is:

$$T_c = T_{amb} + \frac{G \cdot (NOCT - 20)}{800} \tag{2.11}$$

Where,

$T_c = Solar\ cells\ temperature$ [°C]
$G = Solar\ irradiance$ [W/m^2]
$T_{amb} = Ambient\ temperature$ [°C]
$NOCT = Nomina\ operating\ cell\ temperature$ [°C]

I. Single Diode (Ideal) Solar PV Cell Modeling

The single diode ideal model of solar cell refers to the formation of a simple mathematical model which illustrates the behavior of solar PV cells, without influencing resistive losses, environmental effects and recombination processes. It consists of three major parameters such as, photocurrent source, a diode and p-n junction electrical behavior (figure 2.18). The aim of this single diode ideal solar PV cells modeling is to acknowledge maximum efficiency and performance according to the theory with the ideal conditions. This simple model can be expressed by the theory of Skockley diode [38].

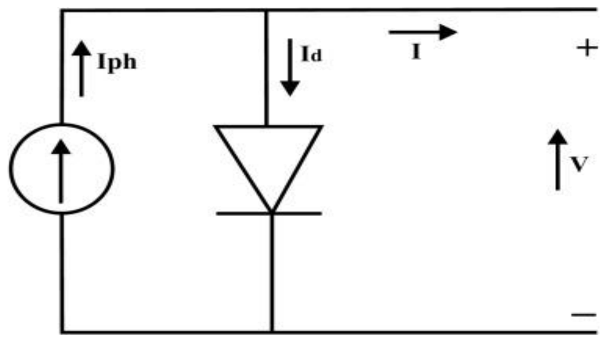

Figure 2.17: Single diode ideal solar PV cells model

The mathematical expression of single diode ideal modeling is:

$$I_d = I_0 \left(e^{\left(\frac{V}{nV_T}\right)} - 1 \right) \tag{2.12}$$

Where,

$I_0 = Saturation\ current$
$n = Ideality\ factor\ of\ diode$ [n=1 ideal diode and n > 1 real diode]
$V_T = \frac{kT}{q}$ (Thermal potential)
$q = Charge\ of\ electron$
$k = Boltzmann\ constant$
$T = Solar\ cell\ absolute\ temperature$
$V = Voltage\ across\ solar\ PV\ cells$

According to characteristic equation deducted from Kirchhoff law:

$$I_{pv} = I_{ph} - I_d \tag{2.13}$$

$$I_{pv} = I_{ph} - I_0 \left(e^{\left(\frac{V}{nV_T}\right)} - 1 \right) \tag{2.14}$$

II. Single Diode Four Parameter Solar PV Cell Model

In this model the equivalent electrical circuit includes a current source with a parallel connected diode that consists of ideality factors to recombination of space charge region [39]. This four parameters model enhances accuracy by series resistance and parallel resistance considered to be infinite. It is the most simple and perfect model to diagnostics solar PV panels with high precision [40]. It has the following parameters: I_L, R_s , n , and I_s.

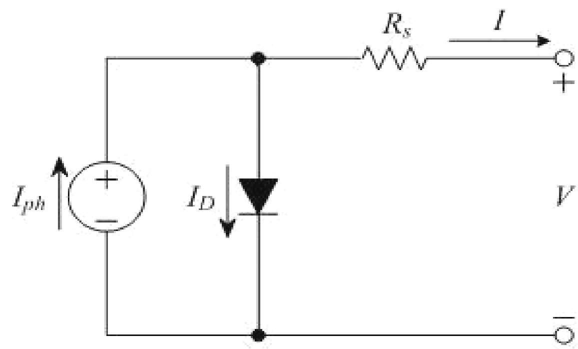

Figure 2.18: Equivalent circuit of four parameters model

The mathematical expression of single diode four parameter PV cell model:

$$I_{pv} = I_{ph} - I_s \left(e^{\left(\frac{qV+qR_sI}{nKT}\right)} - 1\right) \tag{2.15}$$

In the equation, R_s is solar cell series resistance. With the equal irradiance and the temperature of p-n junction conditions, short circuit current equation can be obtained,

$$I_{sc} = I_{ph} - I_s \left(e^{\left(\frac{qR_sI_{sc}}{nKT}\right)} - 1\right) \tag{2.16}$$

When, the voltage V=0.

Also, the open circuit voltage can be expressed by [41]:

$$V = V_{oc} = \frac{nKT}{q} ln\left(1 + \frac{I_{sc}}{I_s}\right) \tag{2.17}$$

When, the current I=0.

Equation of (2.16) and (2.17) represents the I-V characteristic curve of solar PV, under changing resistive load conditions (figure 2.20).

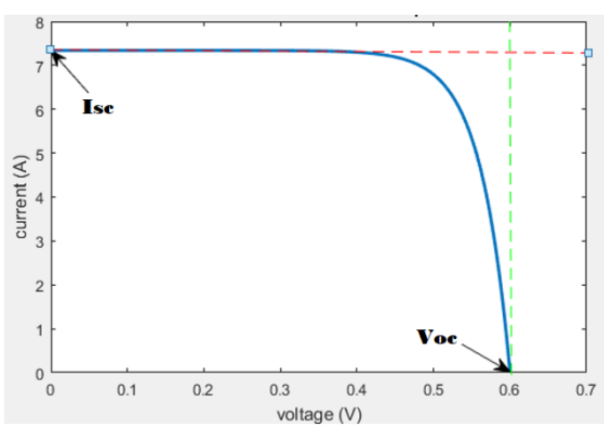

Figure 2.19: Ideal solar cell I-V curve

When the resistance value is small, voltage (V=0) is zero and short circuit current (I_{sh}) of solar cell is maximum. And when resistance value is high current (I=0) is zero and open circuit voltage (V_{oc}) of solar PV is maximum.

III. Single Diode Five Parameter Solar PV Cell Model

The single diode five parameter modeling is also known as real solar cell modeling. To enhance the maximum power from real solar cell, the series resistance (Rs) should be as minimum as possible (milli-ohms) and shunt resistance (R_{sh}) as high as possible. This model represents the actual solar cell behavior [41]. It includes a diode, series resistance, and a shunt resistance.

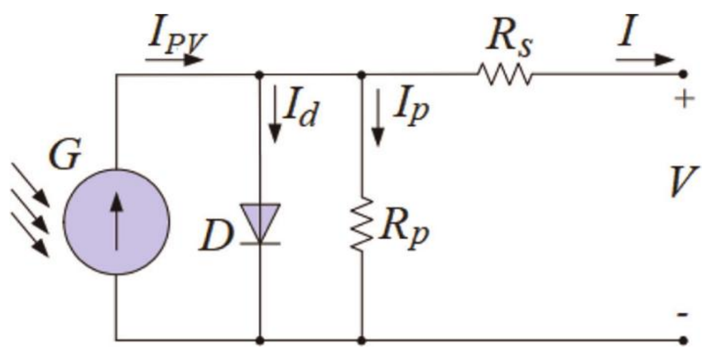

Figure 2.20: Equivalent circuit diagram five parameters model

The mathematical model for five parameters solar cells can be express as

$$I_{pv} = I_L - I_s \left(e^{\left(\frac{qV+qR_SI}{nKT}\right)} - 1\right) - \left(\frac{V+R_SI}{R_{sh}}\right) \tag{2.18}$$

And the equation of the voltage expresses as

$$V = I_L R_{sh} - IR_{sh} + I_s \left(e^{\left(\frac{qV+qR_SI}{nKT}\right)} - 1\right) - IR_s \tag{2.19}$$

The figures 2.22 represent the P-V and I-V characteristic curves for ideal and real solar PV cells.

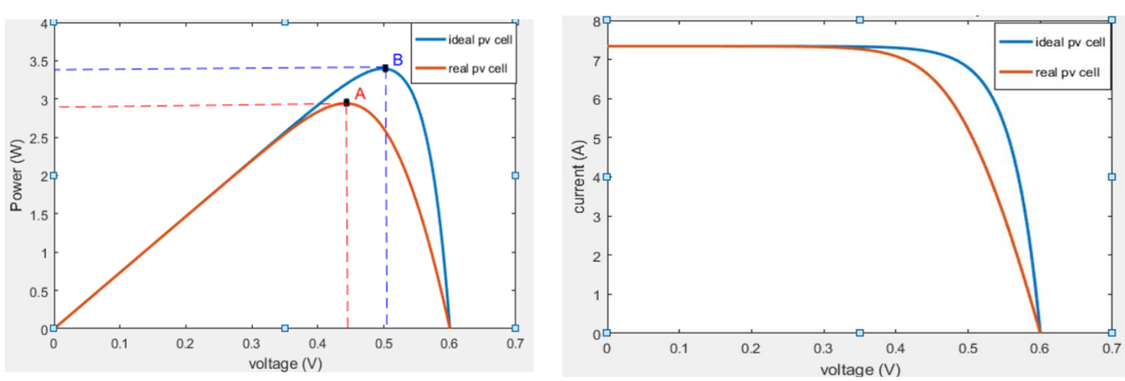

Figure 2.21: P-V and I-V characteristic curves for ideal and real solar PV cells

From the graph it is visible that the ideal solar PV cells generate higher power than real solar PV cells due to the series (R_s) and shunt (R_{sh}) resistance losses.

2.4.4 Influence of Irradiance and Temperature on Solar PV Cells

The solar PV cells efficiency and performance are heavily influenced by two major environmental factors such as light intensity or irradiance and temperature. Those factors are very crucial for shaping the solar PV cells electrical behavior, which directly influences PV voltage, current, and overall energy harvesting.

a) **Influence of Irradiance on Solar PV Cells**

The irradiance is normally measured by watts per square meter (W/m^2), which represents the received sunlight from sun. The solar irradiance is directly proportional to solar PV cell photocurrent ($I_{ph} \propto G$), which opposes to diode current. As solar irradiance raises the number of photons also raises and hatted to the solar cells, as a result the photocurrent of PV cells also rises. Hence it is most influencing external factors for solar PV cells that can change the parameters behavior [41].

The mathematical expression to obtain the variation of short circuit current relation with standard testing condition (STC) is:

$$I_{sc} = I_{sc,STC} \cdot \frac{G}{G_{STC}} \cdot \left[1 + \alpha_{I_{sc}} \cdot (T - T_{STC})\right] \tag{2.20}$$

Where,

$I_{sc} = Short\ circuit\ current\ [A]$
$I_{sc,STC} = Short\ circuit\ current\ at\ STC\ [A]$
$G = Measured\ irradiance$ [W/m²]
$G_{STC} = Irradance\ at\ STC$ [W/m²]
$\alpha_{I_{sc}} = Coefficienct\ of\ short\ circuit\ current\ temperature$ [%/°C or A/°C]
$T = Measured\ temperature$ [°C]
$T_{STC} = Solar\ cell\ temperature\ at\ STC$ [°C]

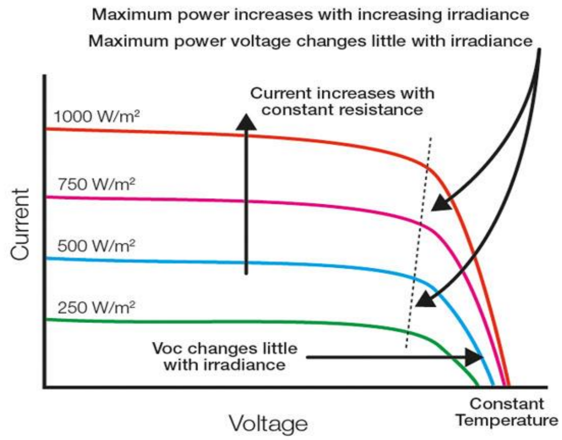

Figure 2.22: Solar PV cell irradiance effect

The figure 2.23 represents, if the solar irradiance changes, there will be small changes of solar PV open circuit voltage (V_{oc}). But the short circuit current (I_{sc}) changes a lot. So, the irradiance has huge influence on short circuit current, and it can strongly influence the solar PV panels overall power generation.

b) Influence of Temperature of Solar PV Cells

Temperature can affect both voltage and current of solar cell. But temperatures influence is more complex than irradiance. Increasing the temperature slightly will increase photocurrent, because it reduces the bandgap energy of the p-n junction material. But it mainly affects solar PV cells open circuit voltage (V_{oc}) [43]. Because the high temperature is the reason to increase recombination of solar cell electron-hole pairs and reduce effective voltage through the solar PV cells.

The mathematical expression to obtain the variation of open circuit voltage relation with standard testing condition (STC) is:

$$V_{oc} = V_{oc,STC} + \beta_{oc}.(T - T_{STC}) \tag{2.21}$$

Where,

$V_{oc} = Open\ circuit\ voltage\ [V]$
$V_{oc,STC} = Open\ circuit\ voltage\ at\ STC\ [V]$
$\beta_{oc} = Coefficienct\ of\ open\ circuit\ voltage$ [%/°C]
$T = Measured\ temperature$ [°C]
$T_{STC} = Solar\ cell\ temperature\ at\ STC$ [°C]

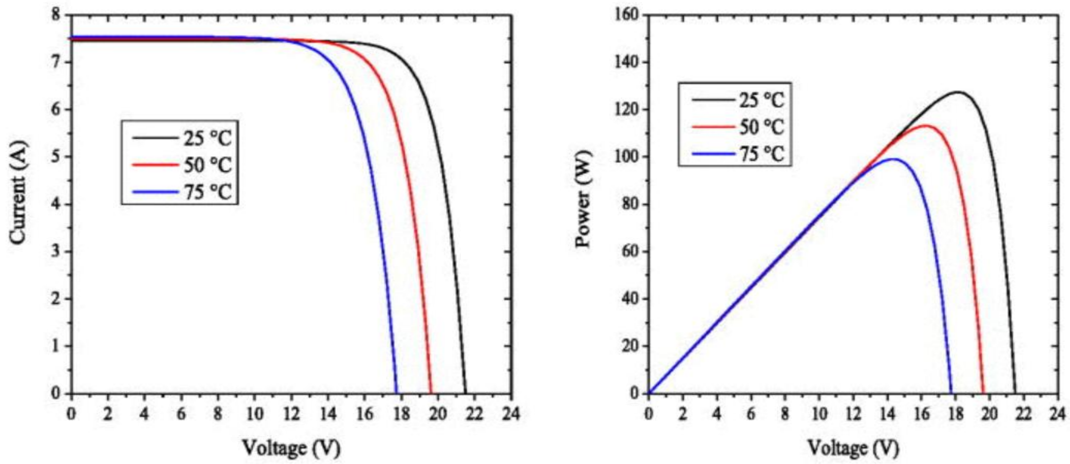

Figure 2.23: Solar PV cell temperature effect

The figure 2.24 illustrates that the temperature has a strong influence on solar PV open circuit voltage (V_{oc}) compared to short circuit current (I_{sh}). But temperature affects both parameters of solar PV cells, and it also has huge influence on overall power generation from solar PV panels.

The maximum solar power is achieved when irradiance is high and should be temperature is low. Although in real world conditions, it is very difficult to get that favorable environment.

2.5 Power Conversion and Control for Solar PV Systems

Due to environment, the photovoltaic (PV) panels exhibit non-linear I-V characteristics. It has a single optimal operating point at any given point of time, which is known as the Maximum Power Point (MPP) under STC (irradiance: 1000 W/m^2 and temperature: 25°C) conditions. There are several techniques exist, that have unique features to optimize the PV panels' performance. PV-to-load connection topologies depend on load characteristics. Optimal efficient converters are essential for interconnecting with photovoltaic (PV) systems to the grid, which can convert and invert (Inverter) low-voltage DC to AC. Some well-known topologies are discussed below.

- **Direct Solar PV to Load Connection:**

The direct connection of solar PV modules to loads is the most cost-effective solution. The operating point of the solar PV panel changes continuously in the direct method. The MPP point of the solar panel depends on the impedance of the loads (DC). The IV characteristic of solar PV and loads both intersect. To protect the reverse current into the PV modules and loads (DC), a blocking diode should be placed. However direct method has the quickest oscillations, slow convergence, and sensitivity to temperature fluctuation. This will cause inefficient energy conversion and reduce energy efficiency.

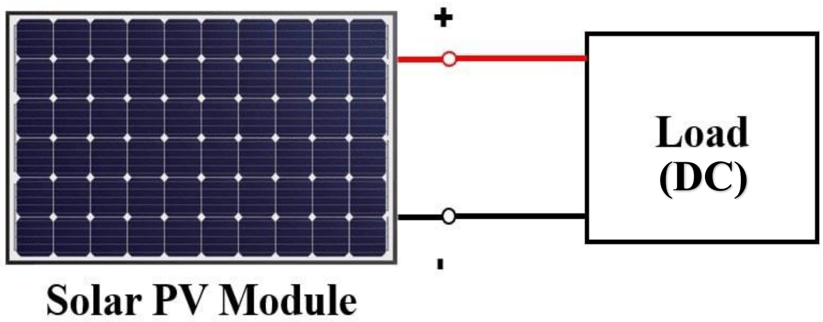

Figure 2.24: Direct Solar PV to DC Load Connection Diagram

The direct solar PV to loads connection can be two types:

1. Battery as DC voltage source
2. Resistive loads

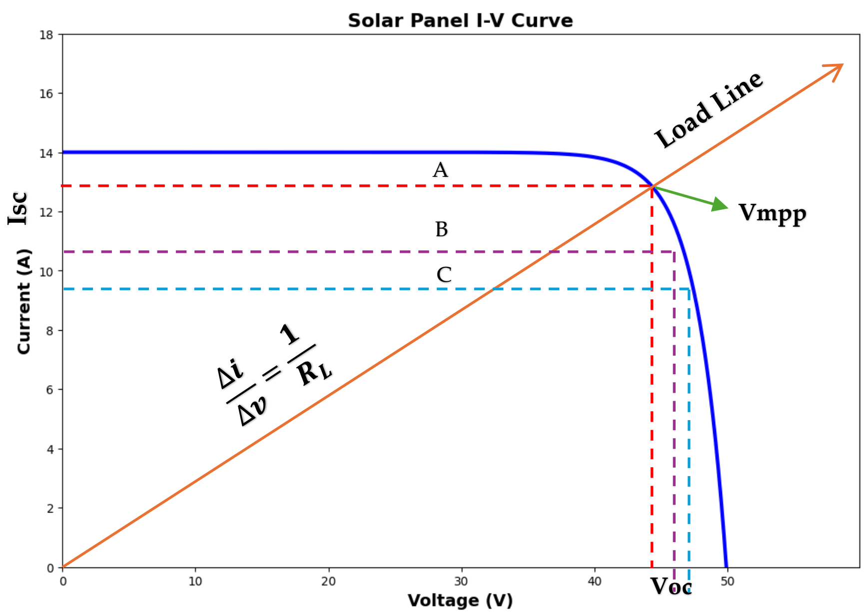

Figure 2.25: Solar PV MPP according with load resistance for direct connection

At different MPP operating points the solar PV module produces different output power. From the above figure 2.26, the point of 'A' will produce maximum power than the points of 'B' and 'C'. The power generation will vary with the changes in irradiance and temperature. Due to higher irradiance, solar PV cell temperature also will increase which is the reason for the decrease in PV power generation.

Maximum power generation from solar PV panels depends on irradiance, temperature, and load resistor variation. To get the maximum power from solar PV panels, the load must match with

PVs MPP. Although in the fixed irradiance and temperature there is one MPP, but in partial shading condition there are different MPP points [44].

To extract the maximum power from the solar PV panel the load resistance should be passed through the MPP point.

$$R_{load} = \frac{V_{mpp}}{I_{mpp}} = f(G, T) \tag{2.22}$$

The best practice is to always keep the load resistance at its optimum point when the irradiance and temperature change. Therefore, the power system must be fulfilled to ensure optimal operation to extract maximum power.

- **Power Conversion Stages:**

To ensure optimal performance and enhance efficiency, a power conversion stage is very crucial. These stages convert DC power to AC power and supply to the loads. The process normally involves multiple steps, such as a DC-DC converter, MPPT algorithm, DC-AC inverter, and grid integration. All the parameters should comply with the standard electrical system. All those steps must be implemented to ensure efficient energy harvest from solar and reduce the losses of an overall reliable system.

2.5.1 DC-DC Converter:

The DC-DC converter is a very essential component for solar energy systems. The converter regulates the voltage and current to ensure solar optimal power transfer. It adjusts the desired voltage and current to maximize system efficiency through the MPPT techniques.

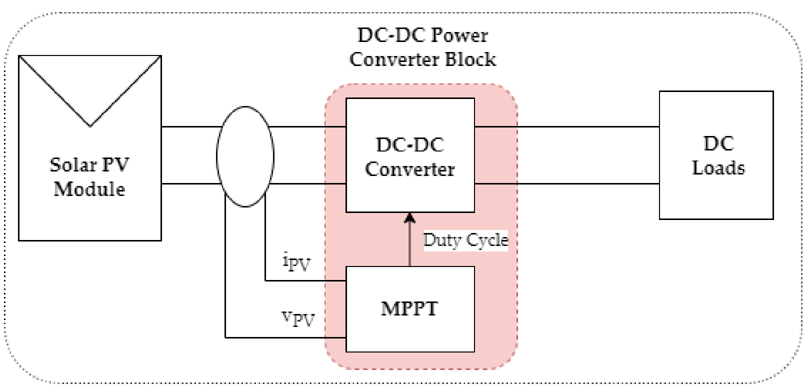

Figure 2.26: Solar PV to DC load connection diagram via power electronic stage [45]

By optimizing the reliable power flow DC-DC converter plays a crucial role in enhancing performance and efficiency. There are different types of converter topology available that can serve the desired output power [45]. The traditional DC-DC converter topologies are mainly two types.

1. Non-isolated Converter
2. Isolated Converter

Non-isolated Converter:

The isolated type of converter represents the electrical barrier within the input and output side of the device. The non-isolated converter is commonly used in the solar energy system due to simple and lower complex systems. The non-isolated converters are Buck (step-down) converter, Boost (step-up) converter, and Buck-Boost Converter.

Isolated Converter:

The isolated converter is also used in solar energy systems that can provide electrical isolation within input and output. The typical isolated converter such as a Flyback converter, Forward converter, Push-pull converter, Half-bridge and Full-bridge converter, etc.

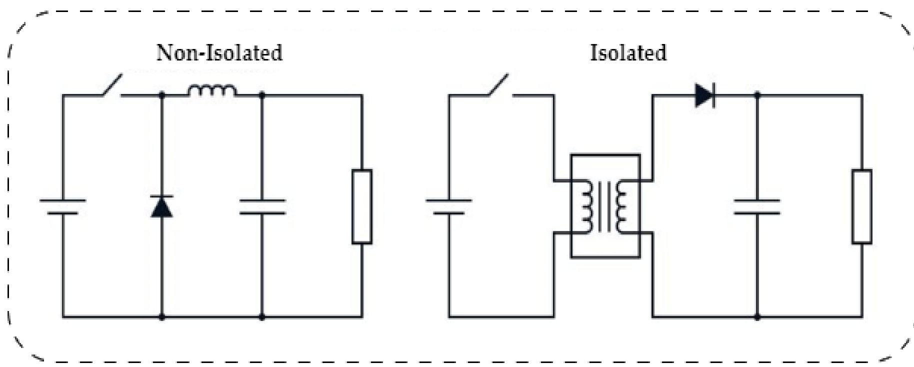

Figure 2.27: Isolated and Non-isolated DC-DC Converter [46]

To implement and extract maximum power from solar PV modules, we consider DC to DC boost converter with MPPT techniques. The boost converter is used as an electronic power conversion stage.

2.5.2 Boost Converter:

The boost converter is a power converter or step-up converter that is used in diverse applications. It steps up the input voltage as required to load. Boost converter contains at least two semiconductors, a diode, and a switching element such as a transistor and one energy storage component (inductor, capacitor) or both. To reduce the ripple of the system a capacitor filter is used [47]. In the applications of power electronic devices with solar PV panels, battery storage systems, laptops, phones, and many more.

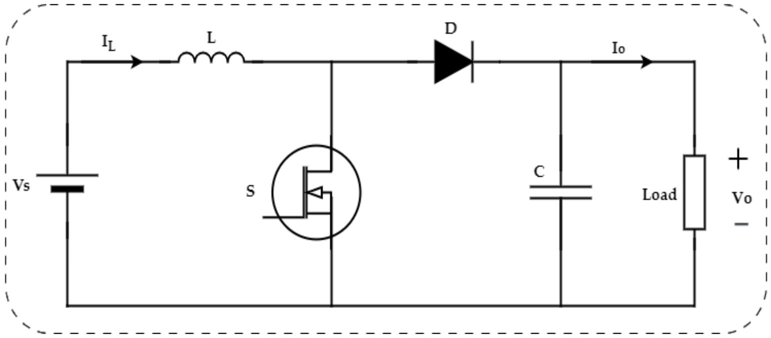

Figure 2.28: Boost converter schematic diagram

The principle of the boost converter is that it resists changing the inductor current by either increasing or decreasing. For a boost converter, the output voltage is higher than the input voltage. It is widely used as the switched-mode power supply (SMPS) where the input voltage does not meet the output higher voltage.

- **Switch ON State Operation:**

During the ON-state operation, input voltage (Vs) is applied through the inductor (L), hence inductor current increases linearly and stores energy as in a magnetic field. Meanwhile, the diode (D) is reverse-biased and prevents the current flow to the load.

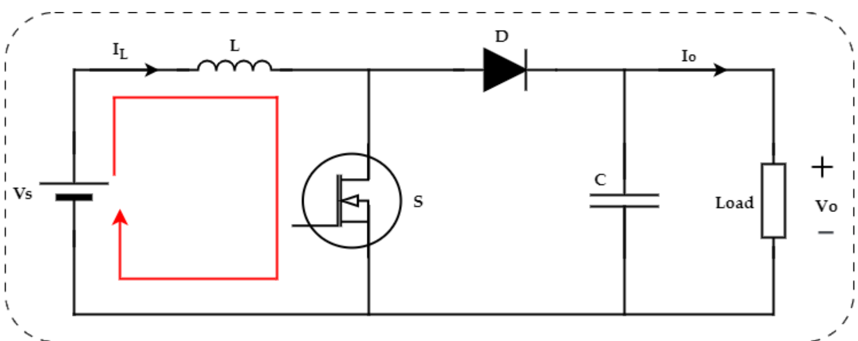

Figure 2.29: Switch ON state operation

The mathematical expressions of the inductor voltage and current are given by:

$$V_S = V_o \tag{2.23}$$

$$\frac{dI_L}{dt} = \frac{V_S}{L} \tag{2.24}$$

Where,

Input voltage: Vs
Output voltage: V_o
Changing inductor current = dI_L
and Inductance = L

- **Switch OFF State Operation:**

During the OFF-state operation, there is no input voltage (Vs), while the inductor (L) releases stored energy to maintain the current flow for continued operation. While an inductor discharges, the polarity of the diode (D) is forward-biased and allows current flow through the load resistor (Vo).

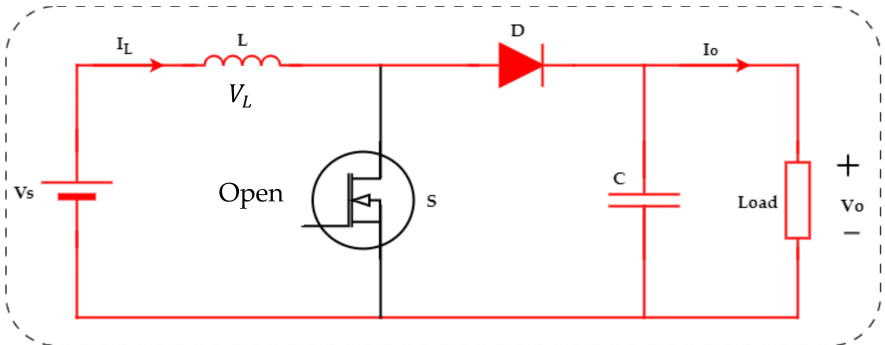

Figure 2.30: Switch OFF state operation.

The waveforms graph for the boost converter is given below.

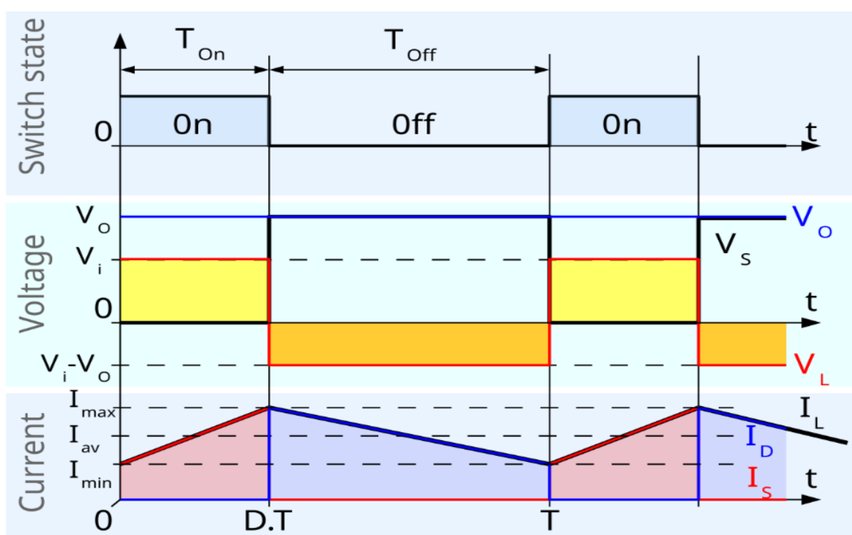

Figure 2.31: Waveforms of the boost converter [48]

The voltage passes through the inductor,

$$V_L = V_s - V_o \tag{2.25}$$

The mathematical expression of the inductor current is given by.

$$\frac{dI_L}{dt} = \frac{V_S - V_O}{L} \tag{2.26}$$

The average value of the inductor voltage (V_L) is zero:

$$< V_L > = \int_0^T V_L dt = 0 \tag{2.27}$$

Then,

$$V_o = \frac{V_s}{1-D} \tag{2.28}$$

$$I_o = I_i\,(1 - D) \tag{2.29}$$

Designing an efficient boost converter depends on the ripple current, which is inversely proportional to the inductance. The equation is given below.

$$L = \frac{V_S \times D}{\Delta I \times f_S} \tag{2.30}$$

2.5.3 DC/AC Converter

Solar PV panels generate direct current (DC) power, while maximum electrical loads require AC power. Hence to fulfill the requirement of AC loads, an inverter must be used to continue supply. An inverter is a power electronic device that converts DC voltage to AC voltage, enabling the integration with solar PV panels. The inverter consists of power electronic switches such as Insulated Gate Bipolar Transistors (IGBTs), Thyristors, or Transistors which provide efficient and reliable energy conversion. Inverter ensures reliable AC power supply to households, industry, and the electrical grids.

2.6 MPPT Algorithms for Solar PV Systems

Maximum Power Point Tracking (MPPT) is a technique that is used in solar photovoltaic systems to extract maximum power by varying the PV panel operation point (MPP). Maximizing the solar PV panels power is significantly affected by the meteorological parameters such as irradiance and temperature. It is very challenging to continuously harvest maximum power, due to different operating conditions. To overcome this challenge, engineers employ MPPT algorithms that always monitor and adjust solar PV modules or array MPP points with the changes of environmental conditions. There are several MPPT algorithms, that are commonly used such as Perturb and Observe (P&O), Incremental Conductance (InCon), Fractional Short Circuit Current (FSCC), Fractional Open Circuit Voltage (FOCV), Fuzzy Logic Control (FLC), Artificial Neural Network (ANN), Model Predictive Control (MPC), Adaptive Neuro-Fuzzy Inference System (ANFIS), Modified P&O (ModP&O), Adaptive Gradient Method (AGM), Ant Colony Optimization (ACO) [49-53]. Among those, four algorithms have been evaluated for their broad applicability, cost-effectiveness, and reliability with the goal of efficient solutions for optimizing solar energy generation. For our research, four of the most used MPPT algorithms are discussed below.

2.6.1 Perturb and Observe (P&O) Algorithm

The perturb and Observe (P&O) algorithm is a fundamental method that is widely used in photovoltaic systems to optimize energy harvesting. The P&O algorithm is easy to implement with hardware systems and commercial utilization. This method perturbates the operating voltage of a PV panel and observes the resulting changes in the power yield. If the energy yield increases with the perturbation, then it continues in the same direction. Conversely, if the energy yield decreases then the perturbation direction is reversed to adjustment [54]. This increase and decrease process helps to identify optimal MPP points, where the solar PV module energy yield is maximum. The table shows the response for the control system.

No. of Case	ΔV	ΔP	$\frac{\Delta P}{\Delta V}$	Tracking direction	Control system response
1	+	+	+	Excellent	Increasing: $V_{ref} = V_{ref} + V$
2	-	-	+	Poor	Increasing: $V_{ref} = V_{ref} + V$
3	+	-	-	Poor	Decreasing: $V_{ref} = V_{ref} - V$
4	-	+	-	Excellent	Decreasing: $V_{ref} = V_{ref} - V$

Table 2.1: The behavior of the control system for each case of P&O MPPT

The principle of the P&O algorithm is to increase or decrease the solar PV module or array output voltage, adjusted periodically by the duty ratio (d) by using a DC to DC converter. This process is referred to as “perturbation” and the direction of solar PV output power is adjusted after “observation”.

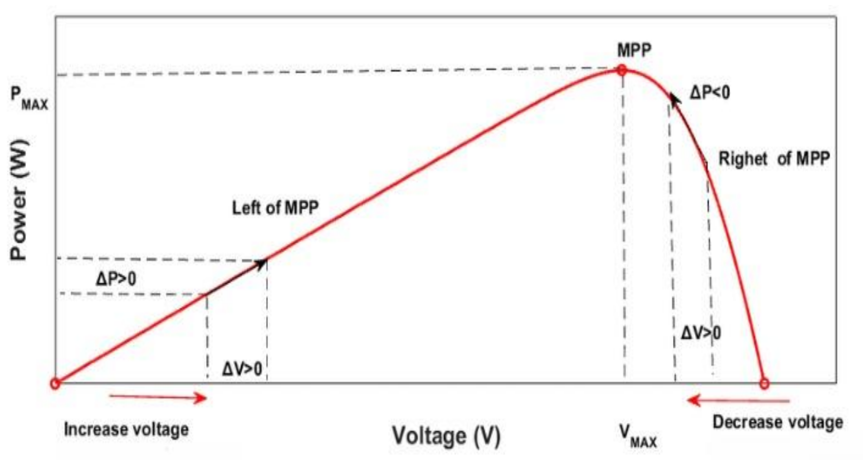

Figure 2.32: Different possible cases for P&O MPPT algorithm [55]

When increasing the voltage of PV panels, the power will increase as well. During this period the PV module operating point on the left of MPP is shown in figure 2.33. Therefore, perturbation continues to increase the voltage and observe, if it still increases then it will change new MPP point which produces maximum power. Moreover, if the voltage decreases and the power is also decreased that means the operating point of the PV module is on the right side in figure 2.33. In this situation perturbation goes back to the previous voltage and observes the power is increased or decreases and compare which one is producing more power. If the previous MPP point produces more power, then the algorithm will keep on that MPP point.

The utilization of the P&O algorithm has the benefits of precise and speedy response which may help to harvest maximum power from solar PV modules. It also has some drawbacks such as high oscillations near MPP points, slow tracking of weather conditions, less efficiency for partial shading conditions, etc. For better understanding figure 2.34 shows the flowchart of the perturb and observe (P&O) algorithm.

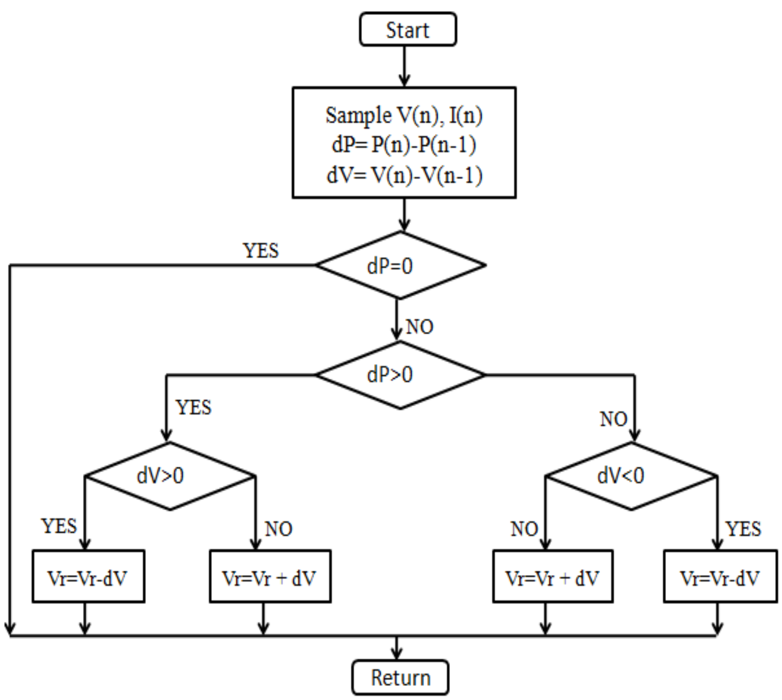

Figure 2.33: The flowchart of P&O MPPT algorithm [39]

5.6.2 Predictive Control Method (PCM) MPPT

The predictive control method for maximum power point tracking is a modern technique that maximizes solar PV panel power generation. The PCM technique is a mathematical model-based prediction, that adjusts the MPP operating point and generates maximum power by predicting future performance. Unlike perturb and observe (P&O) and incremental conductance (IncCond) conventional techniques. The method analyzes PV panel voltage, current, and weather conditions to predict PV panel behavior for optimal control, which ensures it can operate near to MPP point. Also, the PCM algorithm minimizes control framework error for reference and next-step sampling interval. To predict control parameters, discretization methods such as Euler are mostly used [56]. It has high accuracy, but computational complexity is also high. The mathematical expression for low order system is given below.

$$\frac{di}{dt} \approx \frac{i_{(k+1)} - i_{(k)}}{T_s} \tag{2.31}$$

Equation (13) is derived by the Euler method which is the output current expression while removing the inductor voltages.

$$\frac{i_{(k+1)} - i_{(k)}}{T_s} = \frac{1}{L_f}(V_{inv} - V_{grid(k)} - R_{Lf}\, i_{(k)}) \tag{2.32}$$

Hence the prediction equation expression can be.

$$i_{(k+1)} = \left[\frac{T_s}{L_f}\,(V_{inv(n)} - V_{grid(k)} - R_{Lf}\, i_{(k)})\right] + i_{(k)} \tag{2.33}$$

The block diagram of the predictive control method is presented in figure 2.34.

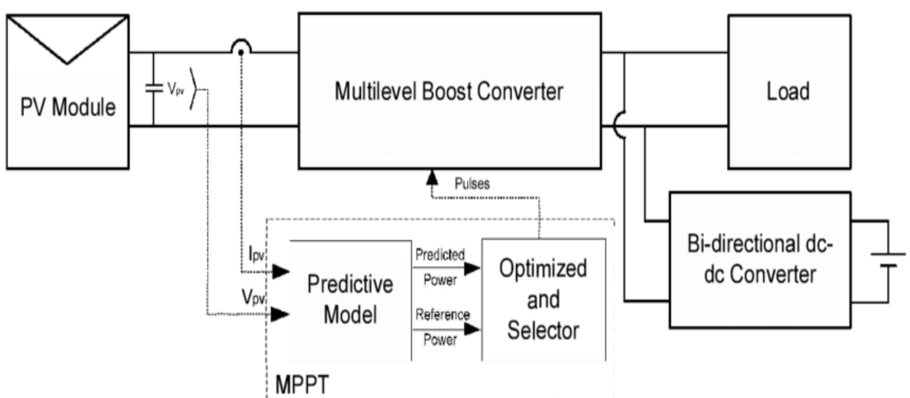

Figure 2.34: The schema of PCM-based MPPT [57].

The PCM method has advantages to enable rapid response to changing conditions such as solar irradiance and temperature that can reduce oscillation than conventional MPPT algorithm. While it offers high efficiency, dynamic response, and stability. PCM has some drawbacks such as complex mathematical models for accurate system modeling, and high compositionality. This predictive control-based model is mostly used for hybrid systems or grid-connected systems, where adaptability and precision are crucial.

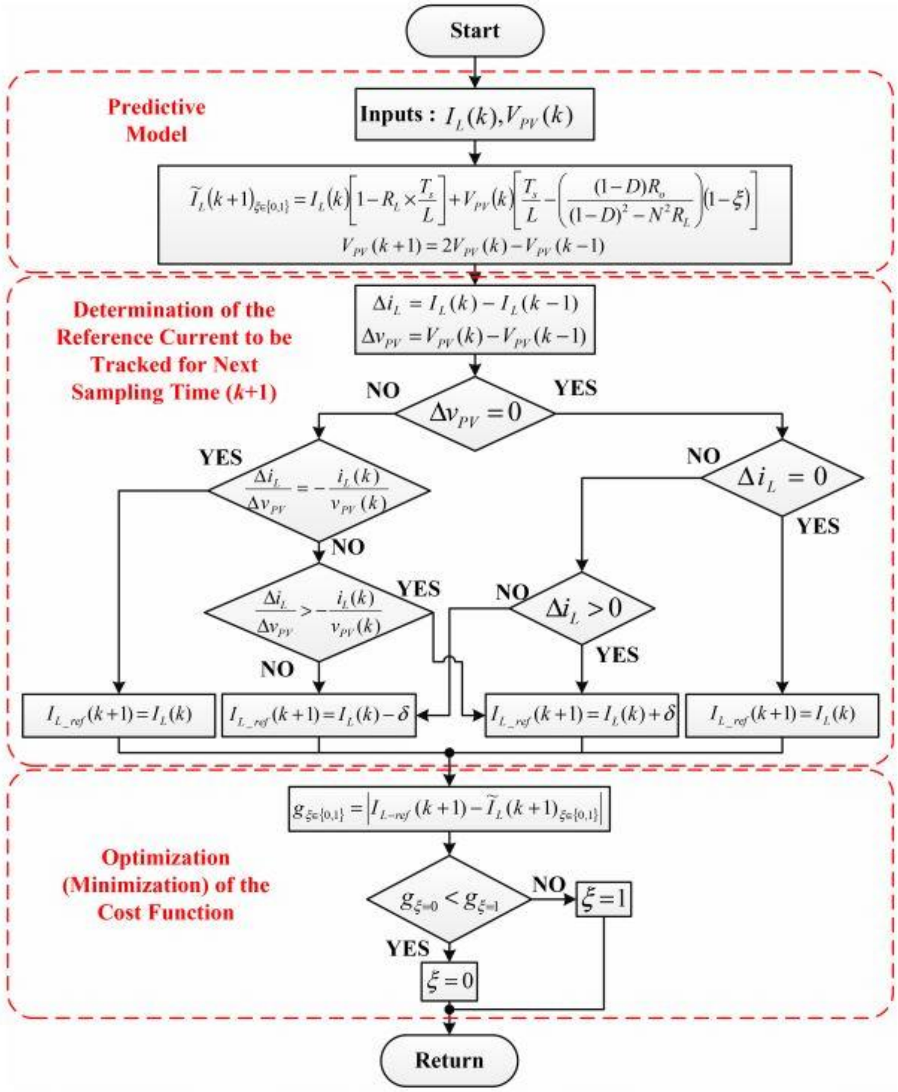

Figure 2.35: The PCM-based MPPT flowchart [57]

2.6.3 Fuzzy Logic MPPT Algorithm

The fuzzy logic MPPT is a modern technique to track the maximum power points (MPP) for solar PV and wind systems. This method can handle inherent changeability and uncertainty of weather conditions. This method is unlike a conventional algorithm that depends on complex mathematical models and precise measurement. It utilizes a heuristic approach that allows to process of input variables such as irradiance and temperature with prominent adaptability. The fuzzy logic algorithm has three main steps Fuzzification, Inference System, and Defuzzification.

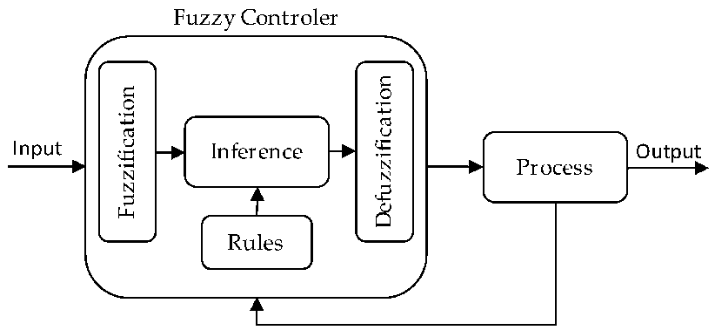

Figure 2.36: Block diagram of fuzzy controller [58]

- **Fuzzification**: In fuzzification, it takes numerical input (changing voltage and power) and converts it into fuzzy variables. To do fuzzification it uses linguistic terms such as 'Positive Large', 'Positive Small', 'Negative Small', and 'Negative Large'. All those variables illustrate quantitative conditions rather than required values, which make the system noise and variation tolerant.
- **Inference System**: The rule-based inference system, where the set of predefined regulations typically IF-THEN statements determines the system response to diverse conditions.

For instance:

- IF the condition of changing power is 'Positive Large' AND changing voltage is 'Positive Small' THEN it will increase the duty cycle.
- IF the condition of changing power is 'Negative Small' AND changing voltage is 'Negative Large' THEN it will decrease the duty cycle.

E \ CE	NL	NS	ZE	PS	PL
NL	PL	PS	NL	NS	NS
NS	PS	PS	NL	NS	NS
ZE	NS	NS	NS	PL	PL
PS	NS	PL	PS	NL	PL
PL	NL	NL	PL	PS	PL

Table 2.2: Fuzzy logic rules for MPPT controller

- Defuzzification: It is the process of transforming fuzzy outputs and converting them into crisp numerical output values as like adjustment of DC-to-DC converter duty cycle. This adjustment secures the system movement into exact MPP. The mathematical expressions for two input variables are given below.

$$E(k) = \frac{P(k)-P(k-1)}{V(k)-V\,(k-1)} = \frac{\Delta P}{\Delta V} \tag{2.34}$$

$$CE(k) = E(k) - E(k-1) = \Delta E \quad (2.35)$$

$$D(k) = D(k-1) + \Delta D(k) \quad (2.36)$$

Where,

E(k) = Identify the location of MPP from the slope of the P-V curve

CE(k) = Verify if the movement of the MPP direction aligns with an operating point or not.

D(k) = Duty cycle, where ΔD can be positive and negative depending on the MPP location.

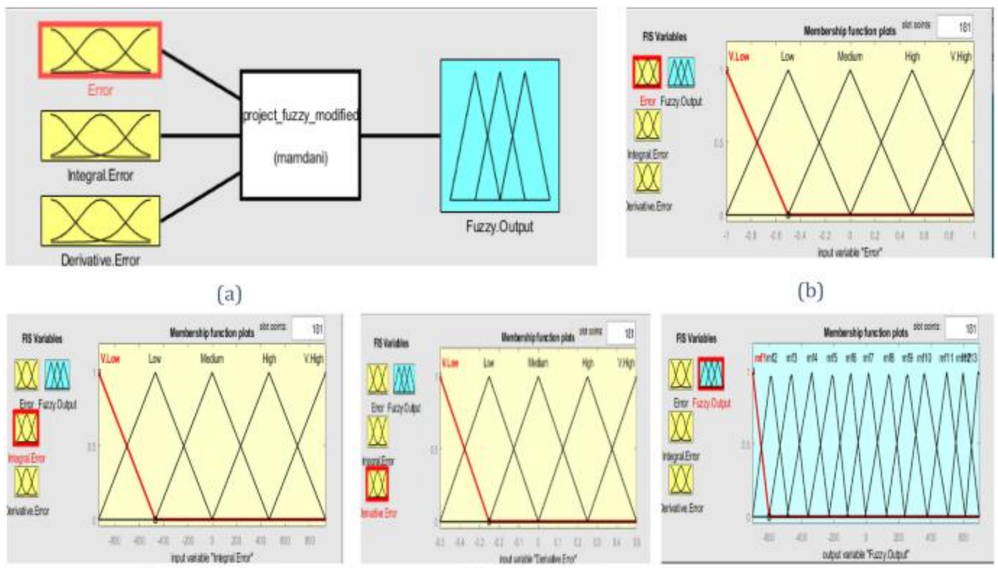

Figure 2.37: Membership functions of errors and increment of duty cycle.

This method can adapt rapidly to changing conditions (irradiance, temperature, wind speed) which ensures precise MPP tracking and optimal performance. It can reduce oscillations near MPP and improve system efficiency. It also has some drawbacks like complex fuzzy logic design, required robust membership function, and rules that ensure optimal system performance.

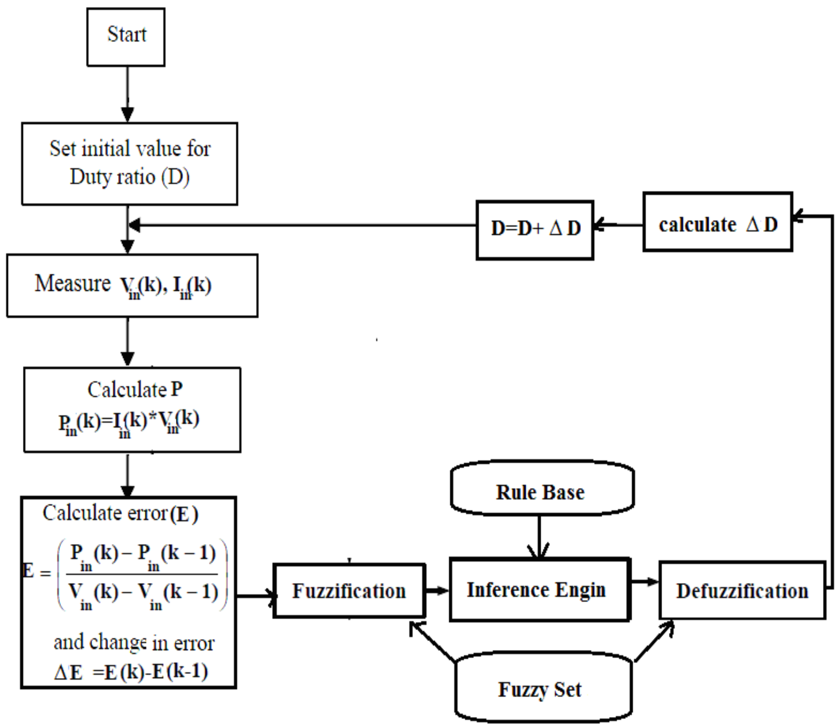

Figure 2.38: The flowchart of fuzzy logic MPPT [59].

2.6.4 Artificial Neural Network (ANN) MPPT Algorithm

Artificial Neural Network (ANN) is one of the most advanced techniques in the range of artificial intelligence (AI). Unlike traditional MPPT algorithms, ANN MPPT has capability to handle complex patterns, learn from big dataset, and prediction. ANN models are very useful for research fields such as function fitting, optimization, machine and deep leaning. ANN-based MPPT algorithm is very useful to handling rapid environmental changes, quick response time, and tracking solar PV maximum power point (MPP). It is one of the fastest responses MPPT techniques. ANN MPPT employs a data driven technique that mimics human neural networks [60]. This MPPT technique is especially effective for extreme environmental conditions, where solar irradiance and temperatures are rapidly changes. ANN-based MPPT are not very common to use, because of computational complexity.

Principle of the Operation

The main principle of this ANN MPPT algorithm is to use complex nonlinear relationship among solar irradiance, temperature and maximum power point (MPP) of solar PV system. The artificial neural network is trained utilizing long term historical dataset to learn the data patterns and make the relationship with the govern of MPP under extreme conditions. Once data is trained, the ANN MPPT can predict MPP of solar panels based on real world environmental inputs, that allow the MPPT system to adjust operating point rapidly and effectively.

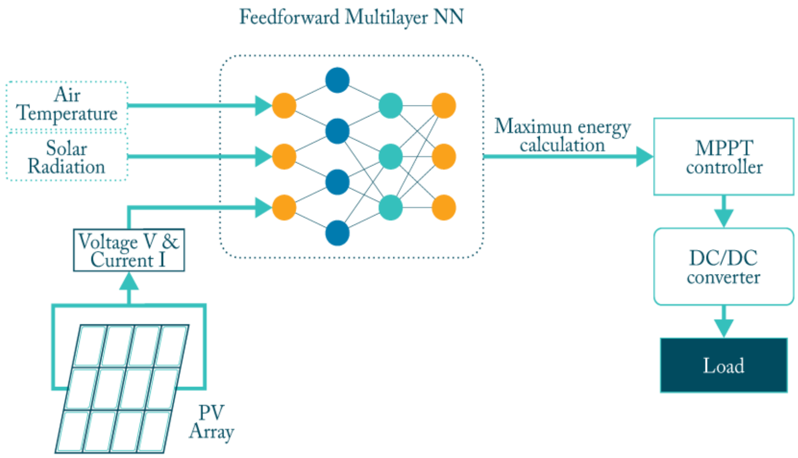

Figure 2.39: Artificial neural network architecture [61]

ANN MPPT Algorithm Components

1. **Data Collection and Processing:**
   - **Input Variables:** The preliminary variables for the ANN-based MPPT includes solar irradiance, and temperature. More variables can be included like wind speed, humidity etc. These input variables are continuously analyzed and measure data, then fed into neural networks.
   - **Output Variable:** For MPPT output variable is duty cycle for DC-DC electronic converter, that controls solar PV panel operating voltage to track the maximum power point (MPP).

2. **Neural Network Architecture:**
   - **Input Layer:** In this layer collect environmental data such as irradiance and temperature.
   - **Hidden Layer:** One or multiple hidden layers process the environmental input data utilizing activation functions that capture the nonlinear relationship.
   - **Output Variable:** This layer give the predicted duty cycle for DC-DC power converter.

3. **Training the Neural Network:**
   - **Training Data:** Long term historical environmental conditions data and corresponding MPP are used to train the neural network.
   - **Backpropagation:** The backpropagation algorithm is used to adjust the weights of neural network and minimizes the error among predicted and actual MPP.
   - **Validation and Testing:** The trained ANN model is validated and tested using different datasets to ensure model accuracy and reliability.

Mathematical Expressions of ANN MPPT

1. **Weighted Sum Calculation**:

$$Net_j = \sum_{i=1}^{n} W_{ij} X_i + B_j \tag{2.37}$$

Where,

X_i = Input parameters such solar irradiance, temperature, voltage and current

W_{ij} = Weight related with each input

B_i = Bias term

Net_j = Weighted sum for neuron j

2. **Activation Function (Sigmoid/Tanh/ReLU)**:

$$f(Net_j) = \frac{1}{1+e^{-Net_j}} \tag{2.38}$$

3. **DC to DC duty cycle adjustment**:

$$D_{new} = D_{old} + \Delta D \tag{2.39}$$

Where ΔD is changing a duty cycle for DC-DC converter by employed ANN MPPT. The ANN-based MPPT algorithm flow chart is given below.

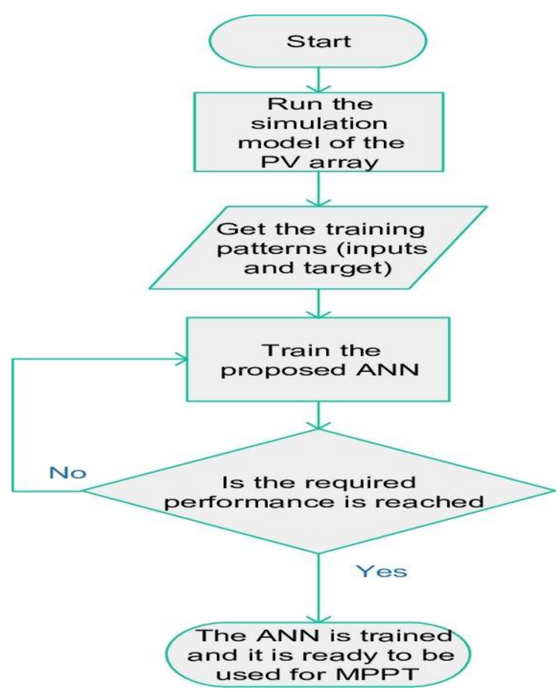

Figure 2.40: The flowchart of ANN-based MPPT [62]

Chapter 3

RE Resource and Demand Forecasting

3.1 Overview of RE Resource and Demand Forecasting

In the context of hybrid microgrid system, renewable energy resource and demand forecasting are the key features to optimize energy use and stability. Diverse renewable energy integration with the modern smart grid or hybrid energy system has significant advantages. But there are lots of challenges also, due to intermittent characteristics of renewable energy sources such as solar and wind energy. Modern hybrid microgrid systems are combined with the renewable energy resources, conventional power generation system and energy storage system (ESS). Where energy generation, energy demand and energy management are essential for overall system reliability. Accurate renewable energy production forecasting plays a vital role in balancing energy demand and supply. It mitigates energy wastage and minimizes the dependency of conventional grids [63]. Whether as, energy demand forecasting ensures to estimate optimal component sizing, and energy management by predicting energy demand patterns. Energy forecasting allows operators to synthesize energy generation, and supply required demand in real time. Both forecasting techniques provide the advantages to optimize the hybrid microgrid system, which ensures generated energy meets the consumer energy demand with maximum renewable energy fraction. By the accurate prediction of renewable energy resources and load demand, hybrid microgrid reduces energy wastage, minimizes operational costs and improve grid resilience.

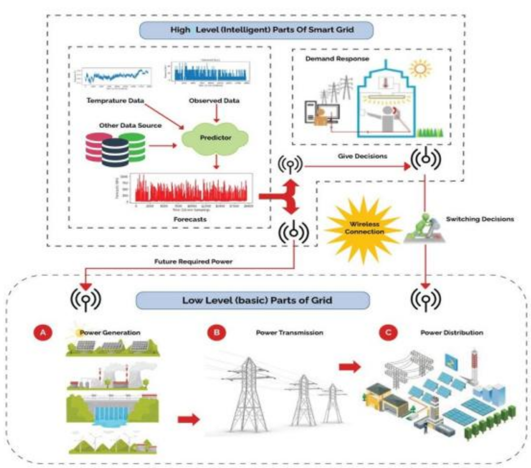

Figure 3.1: Renewable energy generation and demand forecasting [64]

3.1.1 Importance of Accurate RE Resource and Demand Forecasting

Renewable energy resource and demand forecasting are crucial for reliable and efficient energy supply and operation, especially for hybrid microgrid systems that rely on environmental conditions. There are several importances for accurate renewable energy generation and demand forecasting such as:

- **Ensuring Stability and Grid Efficiency:** Accurate renewable energy resource and load demand forecasting, assure the supply aligns with the consumer energy demand. By the predicting renewable energy generation sources fluctuation, the grid operators can make better energy balance of demand and supply. These reduce energy generation costs, and wastage that enhance grid efficiency and stability.
- **Optimize RE Generation Resources:** Accurate and precise energy forecasting ensures optimal usage of renewable energy sources, such as solar PV panels and wind turbines. It minimizes conventional sources like fossil fuel generators and costs which optimize the RE generation.
- **Costs Reduction:** By the prediction of energy generation and consumer energy demand, the grid operators can reduce their operational costs. By utilizing accurate predictions, they can reduce energy storage and fuel consumption costs.
- **Load Management:** Load demand pattern analysis and forecasting helps to find several insights, like peak energy demand, average demand, seasonality, and yearly energy demand variation that allows to make decision for better energy distribution. These predictions ensure overload and underload of grid system and enhance overall performance.
- **Improve Decision Making:** Real time data analysis and forecasting can help to make a better decision or planning or scheduling for energy management. It ensures dynamic adaptation of energy generation, storage and meets the energy demand with the changing conditions.
- **Environmental Impact:** Accurate forecasting and effective utilization of energy, minimize fossil fuels and resilience on conventional grids. Resulting in reducing greenhouse gases (CO_2) emissions and promoting sustainability.

3.1.2. Purpose of Machine Learning (ML) for Forecasting

Machine learning (ML) is a powerful tool that has the potential to forecast in time series. It is not like traditional techniques for forecasting like statistical regression, ARIMA, and SARIMA models. They have limitations to capturing nonlinear pattern complex data. While hybrid microgrid systems often observe nonlinearities of energy generation and demand. Machine learning (ML) model provides more accurate and precise forecasting than traditional statistical models. Especially deep learning models such as Long Short-Term Memory (LSTM), it is a type of recurrent neural network (RNN). It has proven effectiveness for time series forecasting, and capabilities to handle complex variable renewable energy generation and energy demand data. LSTM model can process big dataset with different variables like environmental conditions, energy demand and supply historical data, which offer accurate and precise predictions even uncertainties. Hence LSTM model for renewable energy generation and load demand forecasting are well suited application, where long term and short-term fluctuation trends are related to each other. In the context of hybrid microgrid system, LSTM model provide dynamic optimization, helps to make decisions, and enhances effective energy resource allocation to sustainable grid infrastructure.

3.2 Fundamentals of RE Resource Forecasting

Since the beginning of industrial revolution, most of the country's energy consumption has been dominated by fossil fuels. Diverse fossil fuels are burned and emit toxic gases, that is the major factor in increased global warming and are bad for human health. Whereas renewable energies are the major element for sustainable, cost effective and environmentally friendly energy solution [64]. According to Internation Energy Agency (IEA), the use of renewable energy massively increased nowadays to reduce greenhouse gas emission and enhance sustainability.

a) Resources Analysis (Solar and Wind Energy):

For hybrid microgrid system, we consider primary energy sources would be solar PV panels and wind turbines. Both energy resources are dependent on environmental conditions such as solar irradiance, temperature and wind speed. Solar PV exhibits sensitivity with temperature and reduces energy generation efficiency. On the other hand, wind turbine power generation directly depend on the variation of wind speed. Solar energy can generate maximum power on sunny days, whereas wind may generate maximum energy on windy or cloudy days. The integration of both sources compensates for the consumer demand, enhances resilience on national grid, and ensures sustainable reliability.

b) Analysis of Meteorological Data:

Meteorological data analysis is essential to predict renewable energy generation due to its intermittent nature. Meteorological parameters such as wind speed, solar irradiance and temperature have a close correlation with solar PV panels and wind turbines power generation. By the forecasting model those parameters such as hourly, weekly, monthly and seasonality patterns can be predicted. To analyze these variables of meteorological data, provide better insights of energy generation, and more accurate renewable energy generation prediction of hybrid microgrid system.

c) Variability of RE Resource in Seasonal and Temporal:

Renewable energy resources significantly depend on time, due to diverse fluctuation of environment. Solar PV panels energy generation stick to clear sunny day cycle at noon for peak generation. But it also depends on several variable parameters like, seasonality, sun angle, solar height, and length of the day. Wind energy also varies with seasonal, local weather during the months, and geographical location. To predict accurately, these variabilities analysis are essential which allows hybrid microgrid system energy generation forecasting and ensure stable energy supply even with intermittency of renewable resources.

d) Challenges of RE Resource Forecasting:

Forecasting of renewable energy resources is inherently complex for its intermittent nature. It can be affected by cloud covers, solar irradiance, ambient temperature, while wind energy generation relies on variability of wind speed. Short-term fluctuation of weather induces uncertainties, which makes the prediction model complex. To overcome all these challenges is more complex compared to conventional statistical forecasting models.

3.3 Load Demand Forecasting

3.3.1 Load Demand of Hybrid Microgrid System:

Load demand of hybrid microgrid systems refers to the net amount of energy that is consumed by total connected electrical loads among hybrid microgrid systems over a define time. The load demand included diverse consumers such as residential, industrial and commercial. According to load demands, the application of hybrid microgrid can be designed and installed. The demand loads vary with several factors like, time of the days, week, and season. Others environmental factors can also influence the demand loads, such as temperature, humidity and sudden unwanted situation patterns. Unlike conventional grids, hybrid microgrid systems are designed to integrated with renewable energy sources and fossil fuels based traditional system [66]. Where accurate load demand prediction is very important to meet the consumers demand without any interruption. Consumer load pattern has a complex relationship with renewable energy generation due to rapid variability, also energy storage and backup generator to make decision for dispatch strategies. Optimizing the load demand and generation management provides resilience and system stability.

3.3.2 Load Forecasting for Demand and Supply:

Load forecasting plays a vital role within the operation of hybrid microgrid system. It allows dynamic energy balance of supply and demand. The concept of decentralized energy systems includes accurate demand predictions, which ensure that sufficient energy storage is available to meet daily energy demand of consumers. Load forecasting enhances resilience and minimizes dependency on conventional powered systems, which will reduce the costs and carbon (CO_2) emissions. It also optimizes energy storage scheduling, renewable energy integration, priorities RE's fractions, and strategically store extra available energy during peak hours. Well load forecasting mitigates the system overload and short circuit hazard. The demand load forecasting assures smoother operations, enhances sustainability and stability of grid network. In hybrid microgrid system, load forecasting is used by operators to load management and increase overall system flexibility.

3.3.3 Traditional and Modern ML Techniques for Load Forecasting:

Traditionally load forecasting relies on statistical models, like linear regression, autoregressive integrated moving average (ARIMA), exponential smoothing, and many more. All those models are effective for the simple linear stationary datasets, where relationships of variables are ordinary. In hybrid microgrid systems, where consumer demand can be influenced by diverse complex factors (environmental conditions, energy demand dynamics, etc.). To predict accurately, traditional techniques are not very effective. To deal with these limitations, advanced machine learning (ML) forecasting applications are widely adopted [67]. There are several ML models which are suitable for nonlinear forecasting, such as long short-term memory (LSTM) neural networks, artificial neural networks (ANN), and support vector machines (SVMs). Specially, long short-term memory (LSTM) models are designed to handle long series of historical dataset that has advantages to time series prediction. They can hold past information from time horizon dataset and make them very effective for forecasting demand loads within hybrid microgrid. We consider LSTM machine learning models for energy demand forecasting. This model captures complex energy demand patterns, including diverse weather conditions and dynamically modify predictions with the response of trends. However, ML models allow hybrid microgrid operators to get precise forecasting data and optimize the consumer energy management. ML based demand forecasting also helps to make decisions among hybrid microgrid systems and reduces overall costs.

3.4 Data Collection and Preprocessing

Data collection and processing are the vital steps for data driven projects. It can ensure data quality for insightful analysis, which helps to determine mathematical modeling. Data collection is a process to gather raw data from diverse sources, like sensors, databases, surveys and different kinds of IoT or digital platforms related to the project. Data collecting is a crucial step due to finding meaningful insights. On the other hand, data processing is the first step to analysis. This step involves data cleaning, handling missing data, transforming it into standardized format and data scaling, if needed. Data processing ensures stability and eliminates errors, categorized variables, and provides valuable insights [68]. Together, data collection and processing set up a dynamic foundation for precise and effective analysis, which enhances the result quality and reliability.

3.4.1 RE Resource Data Collection and Preprocessing

(i) Overview of Key Variables in RE Resource Forecasting:

This study utilizes photovoltaic geographical information system (PVGIS) nineteen (19) years of historical solar irradiance, temperature and wind speed datasets. This dataset is very essential for solar energy and wind energy forecasting in the context of hybrid microgrid systems. Solar irradiance and temperatures have a direct impact on solar PV power generation. While wind speed is a primary factor that directly affects wind energy generation and overall grid efficiency. With these variables, we can analyze the potential of solar and wind energy availability and their variability over time. PVGIS meteorological dataset is crucial to identify long and short-term patterns for solar and wind energy productions, daily and seasonal fluctuations [69]. By analyzing all those historical datasets, decision makers can forecast and optimize their hybrid microgrid in a more robust and resilient way.

(ii) Historical Dataset of Irradiance and Temperature:

To analyze the feasibility of the location for hybrid microgrid system installation, historical dataset is necessary. We consider satellite PVGSI dataset, that is pointing dataset and freely available in online according to the location. PVGIS is reliable and more accurate data for Europe. Our studies area is in Portugal and PVGIS provides pointing datasets for it, which is recognized by the European Energy Commission [70]. To achieve higher precision, we consider analyzing 15 years of solar irradiance and temperature dataset. For solar energy production, irradiance has the direct influence. While ambient temperature has the influence of PV energy generation efficiency. High temperature of solar PV cells decreases the power output. Together, analyzing these parameters help to accurate energy estimation for solar energy within diverse environmental conditions.

(iii) Preprocessing of Solar Energy Data:

- **Missing Data Handling and Outliers:** In historical dataset, there are often missing values either from electronic sensors malfunction or error and environmental conditions. These issues are essential to addressed for maintaining consistency. Outliers also should be addressed considering the method of interquartile range (IQR), which eliminates skewing forecasts.

- **Data Scaling and Normalization:** Meteorological data such as irradiance and temperature were normalized using the common scale like minimum and maximum normalization that improves overall model performance and convergence. This method assures the contribution of forecasting model proportionately to outcomes.

- **Features Selection and Extraction:** The key features like solar irradiance, temperature, time, and seasonality were selected. Time based features such as daily and monthly hours, which allow forecasting model to determine accurate energy prediction for the day and seasonal fluctuations.

- **Training and Testing Dataset Split:** To complete this process, the solar PV dataset was divided into several steps such as training, validation and testing that can evaluate the model performance. This splits enables ML model to learn from the historical dataset and understand the trends to maximize the predictive accuracy.

(iv) Wind Energy Data Collection and Processing:

Historical datasets of wind speed have significant impacts on wind energy generation. It varies with several factors such as geographic and atmospheric conditions, also altitude, landscape and seasonality. Reliable datasets of wind speed is vital for precise wind energy forecasting and finding potential locations, which make it possible to manage energy storage from different resources within the hybrid microgrid. Long term (19 years) dataset was obtained from PVGIS that has daily, monthly, seasonal and yearly wind speed patterns. This extensive data allows the machine learning model to identify consistent pattern of wind speed that is crucial to optimizing the wind energy integration among hybrid microgrid.

(v) Preprocessing of Wind Energy Data:

- **Data Cleaning and Anomaly Management:** Due to extreme environmental conditions wind speed frequently contains anomaly. To detect anomaly of wind speed, the techniques were applied to determine abnormal readings that can be corelated or excluded. To fill out the missing data suitable interpolation methods are used to ensure data consistency over the historical dataset.

- **Data Scaling and Normalization:** To describe the wind speed range and distribution, the data was standardized for same scale normalization, that reduce the large deviations effect and enhance model response to fine tune the wind speed variation patterns.

- **Feature Selection:** There are several features to forecast wind energy, such as wind speed, wind direction, daily and seasonal, and time-based characteristics. These features are crucial for optimization of wind turbine energy forecasting and operation within hybrid microgrid system.

- **Data Split Model Training and Testing:** As like solar data, wind meteorological dataset also was segmented for model training, testing and validation. This process ensures the model accuracy and adapts new wind speed data which balance renewable energy generation among hybrid microgrid.

3.4.2 Energy Demand Data Collection and Preprocessing

1). Energy Demand Data Collection:

Energy demand reveals the consumption patterns of diverse loads including hourly, daily and seasonal energy demand variations. Energy demand forecasting can make balance of energy production and energy storage, minimize resilience on additional energy resources, and maintain grid stability [71]. It is very crucial for electrical grid management, system design, simulation and analysis. To make the resilience electrical power system, it requires equilibrium within energy supply and demand [72].

2). Preprocessing of Energy Demand:

- **Handling of Missing Data and Gaps**: To maintain the continuity of data, missing values identification is important and proper interpolation methods are needed to fill it. Energy demand, particularly in peak and off-peak hours, is critical to fill the gaps, hence each missing value is carefully addressed.

- **Data Scaling and Normalization**: Energy demand data must be scaled by utilizing min-max normalization to make standard range, which makes it possible to model and learn energy consumption patterns.

- **Feature Selection**: To make energy demand iterative trends, temporal features like hour of the day, week, months and seasonality's are extracted. Aggregated energy demand patterns, like average hourly, daily, weekly, monthly and annual loads are derived to maximize the performance for short- and long-term fluctuations.

- **Data Splitting**: Energy demand was split into data modeling, training, testing and validation. It allows the model for generalization and future demand patterns forecasting, which enable precise energy demand prediction within hybrid microgrid network.

Preprocessing solar irradiance, temperature, wind speed and energy demands are essential for accurate forecasting. All the datasets of renewable energy generation and demands must be clean, normalize, feature selections, and split to enhance the accuracy. To integrate renewable energy and load demand variables have strong foundation of ML based data driven forecasting model within hybrid microgrid system that balance supply and demand.

3.5 Long Short-Term Memory (LSTM) ML Model Fundamentals

3.5.1 Introduction of LSTM Model

The LSTM model is a part of recurrent neural network (RNN), which is well suited for time series prediction for the ability to handle long and short-term dependencies of sequential dataset. To predict renewable energy generation and energy demand, LSTM machine learning models are essential to identify historical patterns and capture complex relation within time like, hourly, daily, weekly, monthly, seasonal and annual cycles [73]. These features make the LSTM model ideal for hybrid microgrid energy generation and load demand forecasting. It can predict the trends and variation of renewable energy generation and energy demand.

A) LSTM Architecture for Time Series Forecasting:

The LSTM machine learning model architecture designed by the memory cells and with gating mechanisms, input, forget and output gates, which control the information flow among the networks. This architecture allows the LSTM model to hold necessary temporal information, to mitigate the issues and explode the gradients that are often resisted in conventional RNNs. For renewable energy and energy demand forecasting, it can recognize recent trends and future trends by cycling patterns.

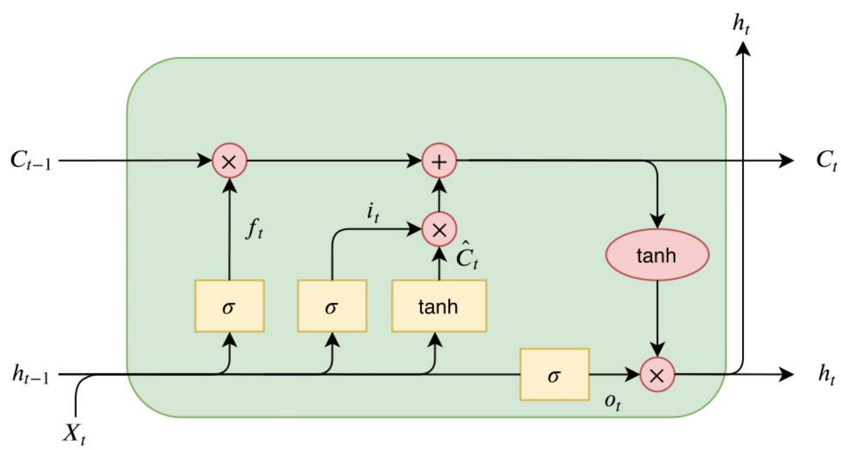

Figure 3.2: LSTM model general architecture [73]

B) Capture Long-Term Dependency in Energy Forecasting:

The machine learning model of LSTM network has the memory to handle sequential dependencies of renewable energy dataset in optimized way. It can hold and refine the temporal data which allows us to manage current and long-term energy trends. LSTM models enable precise predictions of renewable energy fluctuations and energy demand peaks and off peaks. This is pivotal for hybrid microgrid system energy balancing, as its support to predict and adapt to renewable energy generation and energy consumption variations.

3.5.2 ML Model Design for RE Resource and Demand Forecasting

1. LSTM Architecture for RE Resource Forecasting

The LSTM model structured with layers and optimized for the sequential renewable energy resource dataset. The renewable energy resource forecasting model was designed with several features including solar irradiance, ambient temperature, and wind speed. The forecasting model analyzed the variables, which enables correlations with variables over the time. The machine learning LSTM cells has the capability to handle both short term and long-term fluctuations and predict renewable energy generation and thereby helping electrical grid balancing efforts [74].

2. Data Preprocessing for RE Generation Forecasting

- **Normalization:** The input data should be normalized to ensure all the features are on same scale. It will help to rapid convergence and enhance performance.
- **Data Splitting:** To evaluate the LSTM model performance, the data should be split into training, validation and test sets.
- **Sequence Preparation:** To fix the LSTM model format, data must be converted into the same sequential length.

3. Model Architecture for RE Generation Forecasting

- **Input Variables**: Solar irradiance, ambient temperature, wind speed, and time variables (hour, day, month, seasonal). These inputs layer typically used to preprocess the original data.
- **Hidden Layers**: The hidden layer of LSTM model is mainly used to optimize all the parameters and train the dataset.
- **Output Layers**: The output layer used to forecast the renewable energy data according to the LSTM model trained in hidden layer.

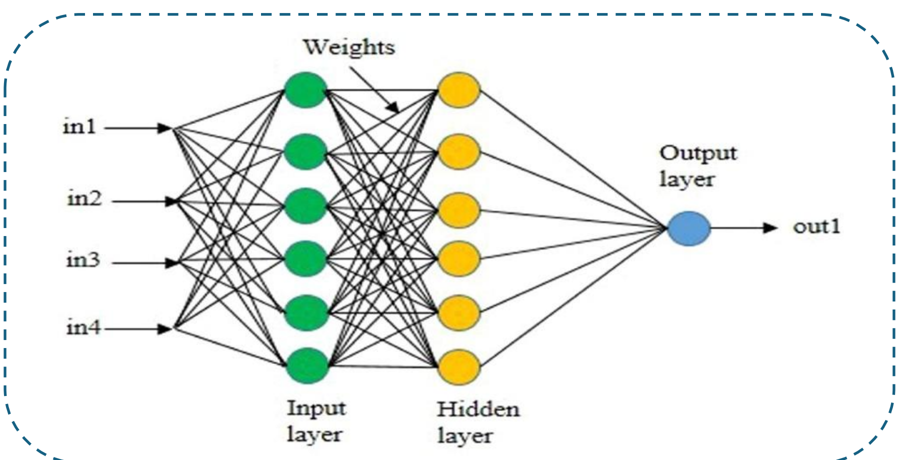

Figure 3.3: LSTM model layers architecture [74]

4. LSTM Architecture for Energy Demand Forecasting

The architecture of LSTM model for demand load forecasting is designed with leveraging historical load demand data. It involves with the prediction of electricity consumption for a region or industries or households. These have various features, such as hourly, daily, monthly and seasonally energy demand patterns, which capture load demand dynamics and trends for accurate forecasting. Accurate energy demand forecasting is crucial for electrical grid management, operations, reliable power supply, and optimal power usages.

4.1 Data Preprocessing for Energy Demand Forecasting

- **Normalization:** The input data should be normalized to ensure compatible scaling.
- **Data Splitting:** Split the energy demand dataset into training, validation and test sets.
- **Sequence Preparation:** Model format must be converted into same sequential length.

4.2 Model Architecture for Energy Demand Forecasting

- **Input Layer:** In this layer capture the historical energy demand data. All those characteristics provide essential information for models, which ensure accurate predictions.
- **Hidden Layer:** Single or multiple hidden layer capture temporal dependencies.
- **Output Layer:** A fully joint layer maps the LSTM outputs to forecast the energy demand for a desired time frame.

5. LSTM Hyperparameter Tuning and Optimization Methods

The hyperparameter tuning is crucial to optimize the model performance, that utilizes grid and random search techniques. The key hyperparameters comprises with learning rate, number of LSTM units, layers, batch size and epochs, which optimize the errors. Initial stopping during the training can help to avoid overfitting, that is optimize algorithm and provide steady convergence for the LSTM model [75].

Hyperparameters to Tune:

- **Number of LSTM Units:** It refers to number of neurons or memory cells in every LSTM layer, that determines ability of network to capture the accurate patterns.
- **LSTM Layer:** It is the depth of LSTM layer, which learn complex model representations.
- **Learning Rate:** It is the step size for every iteration, which synthesizes the model weights during the training and decreases loss function.
- **Batch Size:** Number of training samples processed in a single iteration, before model update it affect model speed and performance.
- **Epoch Count:** It refers to how many times the trained dataset passed through model.

Optimization Methods:

- **Grid Search:** Search all the combinations within the predefined ranges to determine optimal set.
- **Random Search:** Randomly select the hyperparameters from distinct distribution, that is faster than grid search.
- **Bayesian Optimization:** This method utilizes the probabilistic model to predict optimal hyperparameter set.
- **Cross-Validation:** It is evaluating model the model performance, applying the k-fold cross validation to avoid overfitting.

3.6 Evaluation Metrics

(i). Mean Absolute Error (MAE):

MAE is an evaluating metric, which determines the forecasting accuracy with the focus on average absolute error magnitude. It measures the difference within the predicted and actual values.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i| \quad (3.1)$$

Where,

y_i = Actual value

$\hat{y}_i$ = Predicted value

Mean absolute error is simple and easy to understand, also it is less sensitive than the other evaluation metrics.

(ii). Root Mean Squared Error (RMSE):

RMSE metric is effective to evaluate precise prediction, where large fluctuations can impact. It measures the square root difference of average squared, between actual and predicted values.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \quad (3.2)$$

Where,

y_i = Actual value

$\hat{y}_i$ = Predicted value

To evaluate the accuracy of prediction where large data deviation is available, RMSE is very good choice.

(iii) Coefficient of Determination (R^2):

Its measures how the predicted value adjusts the actual value, which indicate proportion of variance in dependent variable from independent variables.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3.3}$$

Where,

y_i = Actual value

$\bar{y}$ = Mean of actual values

To evaluate the overall fit of model to prediction, R^2 is the best suited metric. The value of '1' means the model is best suited and '0' means model is not properly suited.

The evaluation metrics ensure reliability and accuracy for LSTM model, which maximizes overall performance of renewable energy generation and energy demand forecasting.

Chapter 4

Smart Hybrid Microgrid System Modelling and Design

4.1 Introduction

The main aims of this chapter are to model a hybrid microgrid system and design using the software of MATLAB Simulink. Those are the professional software's that are used to make the design, simulate and analysis of all the aspects such as electrical behavior, best possible combination analysis, minimizing cost, enhancing reliability and safety. The hybrid microgrid includes different kinds of renewable energy resources like solar photovoltaic (PV), wind turbine (WT), and energy storage system (ESS). A case study was designed and simulated in MATLAB/Simulink environment considering the multiple energy sources to observe the behavior of SHMs and reveals the best outcomes of the hybrid microgrid system.

4.1.1 Overview of Hybrid Microgrid Systems:

The hybrid microgrid systems are becoming the most essential and effective energy solutions to address the challenges of integrating diverse renewable energy resources with the grid and energy storage system (ESS) for reliable and sustainable energy generation. Due to increasing energy demand and rising global warming and natural climate, the world is trying to shift toward a green energy solution, which reduces resilience on conventional fossil fuel-based energy [76]. Hybrid microgrid system offers a diverse energy solution by combining energy mixed sources, like solar photovoltaic (PV), wind turbine (WT), and energy storage system (ESS) that has the capability to supply constant reliable electricity to diverse applications.

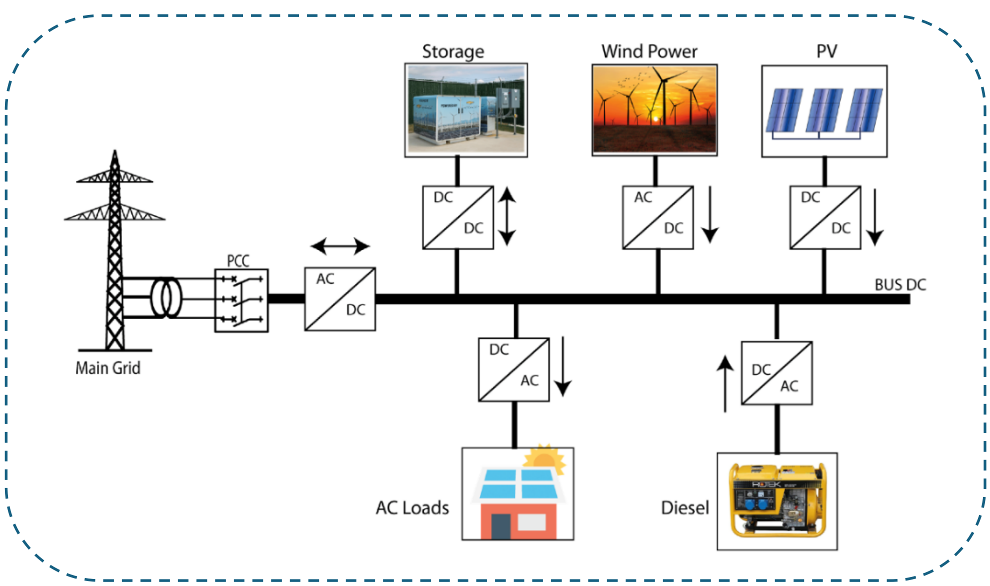

Figure 4.1: Schematic diagram of hybrid microgrid [77]

This hybrid microgrid system has the capability to work both ways either grid connected or off grid connected. Grid connected system can enhance the grid stability and reliability by reducing power fluctuations due to intermittent nature of renewable energy. This system also provides additional services such as peak demand load management, voltage and frequency regulations. In the case of hybrid off-grid system, it enables reliable energy supply, minimizes the dependency on traditional grid and increases energy security [78].

The objective of integrating multiple renewable and conventional energy sources into hybrid microgrid is due to their capability to enhance the system efficiency, resilience, and high reliability. Due to the intermittency of the environment, renewable energy sources such as solar PV and wind are also varying, and their energy production also varies with the changing weather conditions. To mitigate these issues a backup energy storage system (ESS) considered to uninterrupted energy supply. The energy storage system (ESS) store excess energy, when hybrid system generates more power than energy demand that reduces energy costs and mitigates greenhouse gas emission impacts.

The importance of effective hybrid microgrid modeling, and accurate system design are crucial towards optimization and high performance. The optimization of system design requires detailed considerations of feasibility study including daily, monthly and seasonally energy demand patterns, environmental constraint, regional energy prices, and availability of natural resources. Considering all these aspects it can make possible to install a cost-effective and efficient system configuration. This configuration will help decision makers, engineers and researchers to select the best possible energy mixed solution that can operate under diverse environmental conditions [79]. However, this hybrid microgrid system illustrates a pivotal step to reach sustainability and energy resilience infrastructure.

4.2 Hybrid Microgrid Architectures

The hybrid microgrid architecture refers to a diverse energy solution with the combination of DC and AC power systems. Which create flexibility, enhances efficiency and resilience throughout the energy network. The HMG architecture combines multiple renewable and conventional energy sources, for instance solar PVs, wind, traditional power generators and energy storage system (ESS) to assure energy reliability. In our traditional grid system AC can handle the conventional loads, while hybrid system is combined with AC and DC power. For DC grid system renewable energy sources, such as solar, ESS are ideal to supply electricity to DC loads like DC motors, fans, light, electric vehicles etc. The power electronic devices, along with converters and inverters, play a vital role in supplying and managing energy flow within AC and DC sub electrical network [80]. These kinds of hybrid systems are particularly suitable for remote areas and smart grid systems, that offer high performance, reliability, minimize energy losses and maximize renewable energy integration sources.

4.2.1 DC Microgrid System:

The DC microgrid is the substitute of conventional AC grid, especially for the application of direct current (DC) system that is more compatible with the DC loads. In recent years DC microgrid systems have attracted massive research interest. It is the concept of community-based power network or grid. It is not like AC microgrid systems that require power electronic based converter system to convert AC to DC power. DC microgrid systems maintain DC power throughout the electrical network. These systems are gradually deployed to remote areas. Because of its ability to seamless connection with diverse renewable energy sources, which make this system more attractive option for electricity. Nowadays, DC microgrid systems are utilized as distribution networks for automation, industries, communities, manufacturing plants, and maritime system [81]. To minimize the cost of DC microgrid, connection of load distance must be as minimum as possible. The DC microgrid structure included solar PV panels, wind turbines (WT), diesel generators (DG), energy storage system (ESS) and connected with DC buses by the converters and inverters.

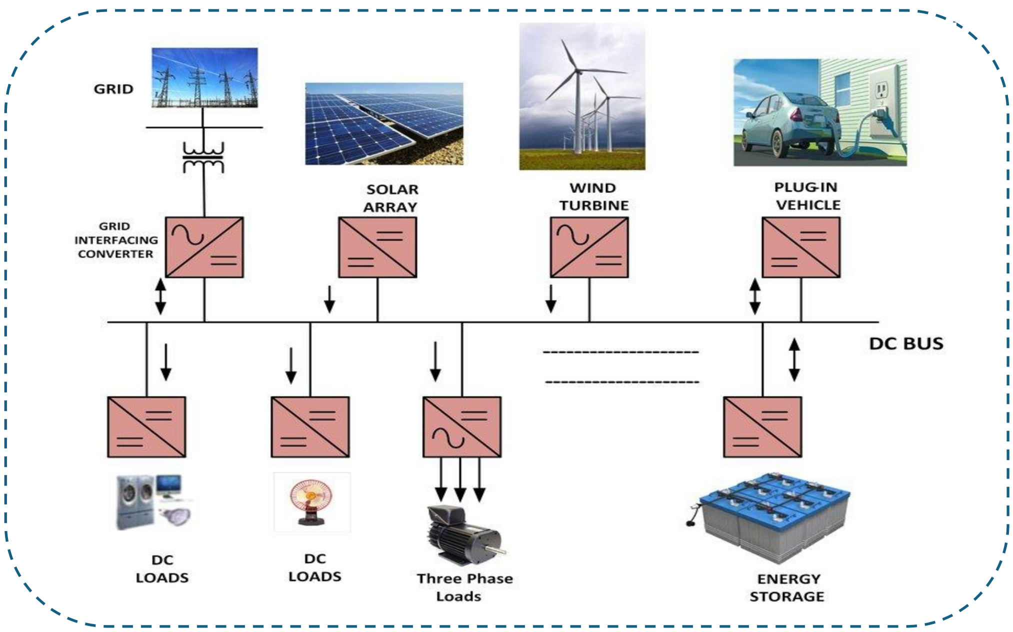

Figure 4.2: DC microgrid system structure [82]

(i). Major Components of DC Microgrid System

A traditional DC microgrid system depends on several major components:

- **Solar PV modules**: These generate the direct current (DC) from the sunlight, and it is an ideal resource for DC microgrids that do not need any conversion process, like AC.
- **Energy storage system (Battery)**: The storage system store the excess energy from DC microgrid, when grids generate maximum power, but the energy demand is low.

Consequently, the battery storage will discharge during the peak energy demand, but low generation. For DC microgrid system these charging and discharging processes will be more efficient, as this system has no need to use a converter AC power to DC power.

- **DC loads:** These are the electronic devices that consume direct current (DC). There are some general examples DC motors, LED lights, laptops, DC fans, mobile phones etc.
- **Converters:** DC to DC converter plays a crucial role to regulate the voltage, which ensures the power supply requirements to match with various components. Converter also simplifies the integration within different voltage levels and DC microgrid system, for instance step up and down of voltage level from batteries and solar PV modules. Which ensure the efficient power flow throughout the grid network and safety. It has the capability to provide isolation between diverse parts of DC microgrid that improve grid protection system and stability.

(ii) Advantages of DC Microgrid System

The DC microgrid system provides several numbers of advantages, specifically for off-grid or remote areas.

1. **Improved Efficiency:** Renewable energy sources such as solar PV panel naturally generate DC power. DC microgrid has less energy conversion process, hence, they do not need any power electronic inverters. Thereby it reduces energy losses and enhances overall system performance.
2. **Simplicity:** DC microgrid architecture is simpler than other microgrid systems, as it has fewer energy conversion processes. It is very easy to install, operate and maintenance of the system, which makes it the perfect choice for remote area application.
3. **Integration with Loads and ESS:** There are lots of modern loads and ESS devices, for instance electric vehicles, battery storage and electronic devices are DC powered. These systems permit direct integration, improve performance and reduce energy transmission losses.
4. **Sustainability:** In isolated or off-grid applications, DC microgrids are very well fitted where maybe the conventional AC grid is absent. Their state forward architecture allows cost effective and reliable energy solutions.

(iii) Challenges of DC Microgrid System

1. **Loss Minimization:** Losses of DC power system are high over long distances. Distance of transmission and distribution in long means will increase the cable resistivity and loss the power. To reduce these losses the cables should be thicker, or the voltage level should be higher, but it will increase the costs.

2. **Voltage Stability:** In DC system maintaining voltage stability is more complex than conventional AC system, specially under loads varying conditions. Often renewable energy fluctuates with extreme environmental conditions. Hence, voltage monitoring systems are required to continuous monitor and regulation, which ensure reliable energy supply and operation.
3. **Standardization:** Towards standardization, for DC microgrid systems still there is no acceptable standard (voltage and frequency) like AC microgrid systems. It has challenges to integrate different manufacturers' components, due to lack of global standardization.

4.2.2 AC Microgrid System:

AC Microgrids refers to AC power supply to grid distribution networks. It is easy to integrate with existing grid networks without any requirements, like power electronic converters and control systems. From the beginning of microgrid concept, it has occupied the main place for research. Due to existing AC grid infrastructure with suitable manner of electrical instruments and electronic appliances [83]. The AC microgrid system is the most adapted and common types of microgrid architecture. It has some advantages such as residential, industrial, and commercial settings, where existing AC systems are already installed. In grid connected conditions, it provides more resilience and high system reliability. This system is highly versatile to both off-grid and grid connected applications. It has the capability to operate independently out of utility grid during power outages.

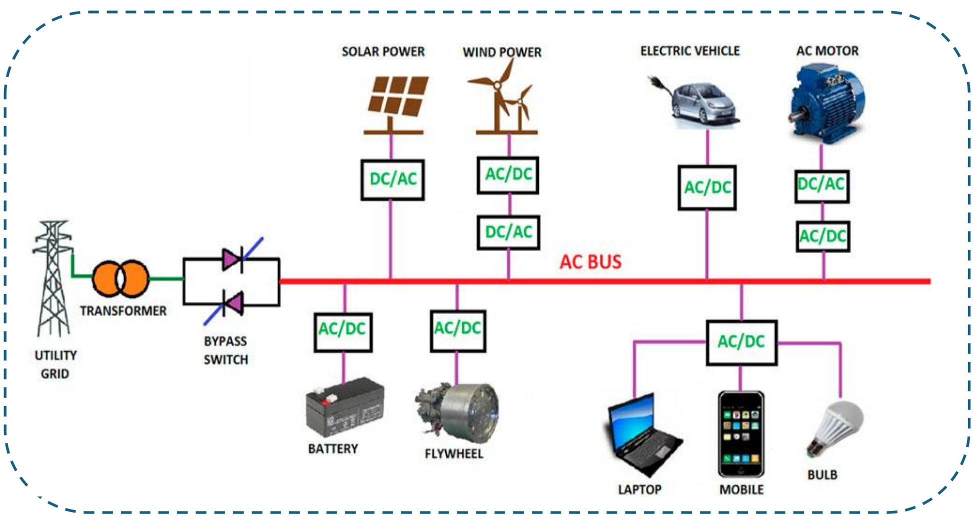

Figure 4.3: AC microgrid system structure [84]

A. Major Components of AC Microgrid System

An AC microgrid system includes several components:

- **AC Generators:** Traditional AC generators like diesel generator (DG) or renewable energy sources like wind turbines, which generate alternating current (AC) and electrify microgrid network.
- **Inverters:** These electronic devices can convert direct current (DC) power (solar PV panels, battery energy storage) into alternating current (AC) power. Inverter ensures compatibility with remote, and grid connected network.
- **AC Loads:** AC loads that consume AC power. The common examples are industrial machines, home appliances and commercial equipment.
- **Transformers:** Transformer is an electrical passive component which transfer electrical power through multiple circuits. It adjusts the voltage levels for AC electricity transmission and distribution. Transformers also ensure the grid and load voltage by stepping up and down and ensures grid requirement or capability.

B. Advantages of AC Microgrid System

The AC microgrid systems are the most common to use and they have several advantages:

1. **Grid Integration:** It can easily integrate with the same types of existing AC utility system. Which allows seamless operation and electrical connectivity.
2. **Developed Technology:** AC microgrid system has recognized global technology and standards for decades. The infrastructures and components are well developed and easily available, which enhances reliability.
3. **High Power Capability:** It can manage a large scale of power transmission and distribution. AC microgrid systems are suitable for heavy machinery or industrial applications (AC machines, motors etc.) and it can meet the high energy demand.

C. Challenges of AC Microgrid System

The AC microgrid system has several challenges to use:

1. **Complex Synchronization:** Synchronization of AC microgrid system with existing traditional grid requires a very precise control system which can handle voltage, frequency and phase sequence. If the control system does not match with grid parameters, the power can damage the equipment.
2. **Reactive Power Management:** AC microgrid system inherently generates reactive power for inductive and capacitive components. To maintain the voltage stability proper power management, it is required to reduce the transmission and distribution losses.

3. **Energy Losses:** In the AC microgrid system power can be lost for transmission and distribution process. Due to the resistance of cable, it creates a barrier to power flow and reduces efficiency for long distance energy transmission.

4.2.3 Hybrid Microgrid (AC/DC) Systems

The hybrid microgrid system is considered to be an advanced energy solution which integrates with AC and DC power flow. It allows energy management, optimize system efficiency, enhance reliability and various types of renewable and fossil fuel-based resources and loads. Conventional AC microgrid has the capability to manage high power over long distance electricity transmission lines. Consequently, DC microgrid system is more effective for renewable energy such as solar PV panels and battery storage system that directly produce and store DC power. The hybrid microgrid system is usually connected in parallel pattern and operates with grid connected and off grid modes [85]. This system is compatible with modern roads, like computer data centers, electric cars, bicycles and so on. Combining AC and DC, increase energy security, enhance performance, minimize costs and reduce energy losses.

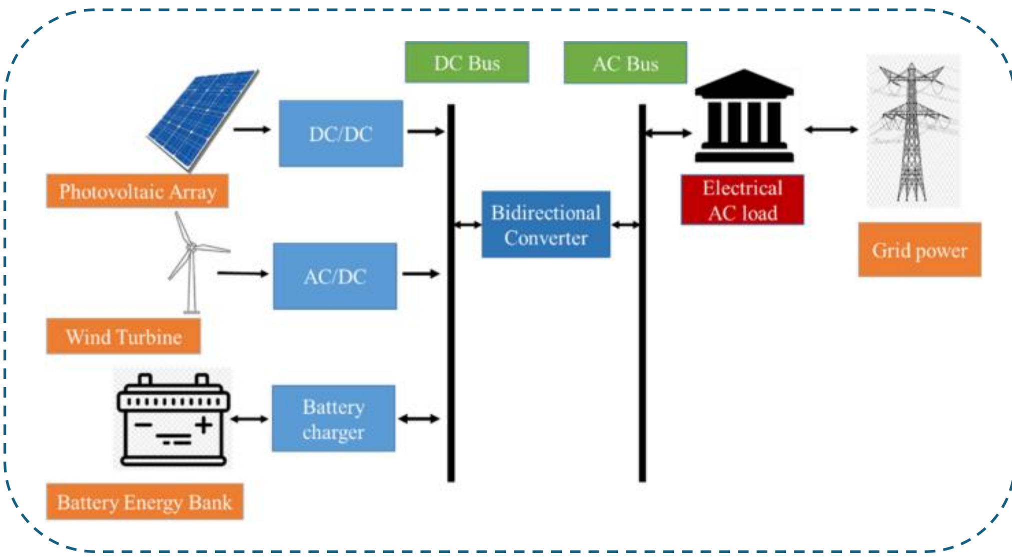

Figure 4.4: Hybrid (AC/DC) microgrid system structure [86]

(a) Advantages of Hybrid (AC/DC) Microgrid System

Hybrid microgrid system has several advantages:

1. **Flexibility:** Hybrid (AC/DC) microgrid system has some great flexibility in diverse renewable energy and traditional energy resources integration, like solar PV arrays, and energy storage systems (battery) where produce and store DC power, on the other hand

diesel generators, and wind turbines produce AC power. This system enables efficient operation and proper utilization of power flow of each load.

2. **Efficiency:** Hybrid microgrid optimizes the component sizing and maximizes the performance. One of the main benefits of this system is, it does not need much energy conversion process. The result is an increase in efficiency.
3. **Resilience and Reliability:** This system can handle both AC and DC power simultaneously, which enhances operational resilience. In the case of failure, for instance AC side, the other side of DC can continue to operate independently which increases entire hybrid microgrid system reliability and performance.
4. **Smart Grids Optimization:** In the application of smart grids system, hybrid (AC/DC) microgrid permit the dynamic energy regulation along with seamless control of different energy generation sources. The modern real time monitoring system provides information on daily energy generation, demand, and grid conditions that enhances optimization performance.

(b) Power Electronics of Hybrid (AC/DC) Microgrid Integration

Power electronics are the main integration instruments of hybrid microgrid systems, which facilitate smooth power flows. Major components are:

- **Inverters:** Solar PV panels and energy storage (battery) system must convert DC power into AC power to integrate the hybrid microgrid system with grid connected loads. The modern inverters are well equipped along with advanced technologies, which can handle power and frequency stability through the hybrid microgrid.
- **Rectifiers:** It allows the energy storage (battery) system for powering the loads from DC to AC source. This is specifically helpful in the case of wind turbines (WT) that produce AC power, while energy storage (battery) system needs to store DC power.
- **DC to DC Converters:** DC - DC converters regulate the voltage levels among the sub buses of hybrid microgrid system, that assure the multiple DC sources and loads can operate at a time with highly efficient manner. For example, according to voltage requirement of battery, DC – DC converter step up and down the voltage level for charging.
- **Bidirectional Converters:** It is crucial equipment for hybrid microgrid systems for smooth energy flow within AC and DC network buses. These ensure power exchange in AC and DC in both directions. Also, it allows us to adapt to the extreme conditions, like renewable energy production and demand of loads fluctuations.

(c) Application of Hybrid Microgrid System in Smart Energy Grids

Modern hybrid microgrids systems have extensive applications range especially in smart grid energy system technologies.

Integration of Smart Grid: Hybrid microgrid systems are very compatible with modern smart grid structures, that require automated and dynamic energy management systems. It enables real time adaptation within AC and DC electrical networks, which optimize power flow and enhance efficiency of energy uses.

Renewable Energy Integration: Hybrid microgrid system has a major application to integrate diverse renewable energy sources. Solar photovoltaic panels, wind turbines (WT), diesel generators (DG), and energy storage system (ESS) can be integrated with same microgrid system with minimal power losses due to less energy conversion process.

Charging Station for Electric Vehicle: Electric vehicles are inherently powered by DC, where hybrid microgrid systems can charge EV's very fast and efficient ways. These do not need any energy conversion, which minimizes the charging times of electric vehicles and increases efficiency.

On-Grid and Off-Grid Applications: These can effectively operate on-grid and off-grid both scenarios. For the application of on-grid system, these can support main utility grid by integrating with renewable energies, that helps to peak shaving and frequency regulation. This system reduces fossil fuel costs and resilience. On the other hand, off-grid microgrid systems supply self-efficient and reliable energy by combining multiple renewable and fossil fuels sources, which ensure continuous energy supply without any utility grid dependency.

4.3 Mathematical Modeling of Hybrid Microgrid System

Mathematical modeling is the crucial foundation for hybrid microgrid design, analyzing and optimizing the overall systems. This modeling method employs multiple mathematical equations which represent dynamics for components, like solar PV panels, wind turbines, diesel generators and energy storage system (battery). Utilizing those mathematical representations helps to evaluate practitioners to analyze the system performance, stability, forecast energy generation and consumption and optimize the operations under extreme environmental conditions.

4.3.1 Mathematical Framework

(I) Modeling Methodologies:

- **State-Space Model Representation:** This method refers to representing dynamic behavior of the system considering state variables, that allows us to analyze how the hybrid microgrid behavior changes over the time [86]. The typical mathematical expression of state-space model is:

$$\dot{x}(t) = \mathrm{A}x(t) + \mathrm{B}u(t) \tag{4.1}$$

$$y(t) = \mathrm{C}x(t) + \mathrm{D}u(t) \tag{4.2}$$

Where,

$x(t)$= State vector
$u(t)$= Input vector
$y(t)$= Output vector
$A, B, C\ and\ D$= Matrices to describe system dynamics

- **Control Theory:** Control techniques like PID and MPC are the crucial to optimizing seamless energy flow and managing stability of the system. Control system performance can be analyzed by feedback loops and standard of stability, that can be developed by mathematical models.

(II) key Equations of Power System:

- **Power Balance:** The mathematical equations of power balance for hybrid microgrid system can be express [87]:

$$P_{gen} - P_{load} - P_{loss} = 0 \tag{4.3}$$

$$P_{PV}(t) + P_{WT}(t) + \ P_{ESS}(t) = P_L(t) \tag{4.4}$$

Where,

$P_{PV}(t) = Solar\ PV\ panels\ output\ [W]$

$P_{WT}(t) = Wind\ turbines\ output\ [W]$

$P_{DC}(t) = Diesel\ generators\ output\ [W]$

$P_{ESS}(t) = Energy\ storage\ (batter)\ output[W]$

$P_L(t) = Overall\ load\ demand\ [W]$

4.3.2 Hybrid Microgrid Components Modeling

(1) Solar PV Panel Modeling

In hybrid microgrid system, solar PV panels are the key components which require accurate mathematical modeling to getting optimal performance. Solar PV panels output power generation depend on environmental conditions, such as irradiance (W/m^2) and temperature (°C). Considering those issues [88], solar PV panels' output power can be expressed by:

$$P_{PV} = P_{max,STC} + \frac{G_{actual}}{G_{STC}} [1 - \beta(T_{actual} - T_{STC}] \quad (4.5)$$

Where,

$P_{PV} = Solar\ PV\ panels\ output\ [W]$

$P_{max,STC} = Solar\ panel\ maximum\ power\ outptu\ at\ STC\ [W]$

$G_{actual} = Solar\ irradance\ at\ current\ time\ [W/m2]$

$G_{STC} = Solar\ irradiance\ at\ STC[W/m2\ or\ 1000W/m2]$

$\beta = Temperature\ coefficienct\ [-\%/°C]$

$T_{actual} = Actual\ temperature\ of\ solar\ PV\ panel\ [°C]$

$T_{STC} = Solar\ PV\ panel\ temperature\ at\ STC\ [°C\ or\ 25°C]$

(2) Solar PV Panels Performance and Effect Parameters

To identify the solar PV panels' performance the key parameters are:

- **Efficiency:** Solar PV panels efficiency refers to ratio of sunlight converted into electrical energy. Considering efficiency, we can identify effectiveness of solar PV panels. In standard testing condition (STC), solar irradiance 1000 W/m^2, cell temperature 25°C, and air mass 1.5. The efficiency express can be:

$$\eta = \frac{P_{output}}{P_{input}} \times 100\% \quad (4.6)$$

- **Fill Factor (FF):** Using the measurement of fill factor, identify the quality of solar PV panels. The expression of fill factor can be:

$$FF = \frac{P_{max}}{V_{oc} \times I_{sc}} = \frac{V_{mpp} \times I_{mpp}}{V_{oc} \times I_{sc}} \quad (4.7)$$

- **Temperature Coefficient of Solar Cell Power:** Typically, a solar PV panels power output increases when temperature decreases. Usually, silicon based solar cell temperature coefficient within -0.3% to -0.5%/°C. The mathematical expressions can be:

$$P(T) = P(T_{STC}) \times [1 + \gamma P \times (T - T_{STC})] \quad (4.8)$$

- **Temperature Coefficient of Solar Cell Voltage:** There is a relationship with temperature and open circuit voltage of solar PV panels. With the increase of temperature, open circuit voltage will decrease. The mathematical expressions can be:

$$V_{oc}(T) = V_{oc}(T_{STC}) + \beta_{v,oc} \times (T - T_{STC}) \quad (4.9)$$

- **Temperature Coefficient of Solar Cell Current:** While solar cells increase the current, simultaneously temperature also increase, but less than the open circuit voltage. Although the solar PV panels loss power. The mathematical expressions can be:

$$I_{sc}(T) = I_{sc}(T_{STC}) \times [1 + \alpha_{ISC} \times (T - T_{STC})] \quad (4.10)$$

(3) Wind Turbine Modeling

Modeling a wind turbine is a pivotal part of hybrid microgrid systems. The objective of modeling is to understand the behavior of wind turbines and predict their energy output under diverse wind speed conditions. The modeling also involves physical dynamics, such as energy conversion, kinetic energy into electrical energy generation. The mechanical power generation of wind turbine relies on some factors, such as wind speed, characteristic of rotor, and efficiency [89]. The mathematical expression can be:

$$P_{wind} = \frac{1}{2}.\rho.A.v^3.C_p(\lambda,\beta) \quad (4.11)$$

Where,

$P_{wind} = Wind\ turbine\ output\ [W]$

$\rho = Air\ density\ [kg/m^3]$

$A = Rotor\ swept\ area\ (\pi \cdot R^2)\ [m2]$

$v = Wind\ speed\ [m/s]$

$C_p(\lambda,\beta) = Power\ coefficient$

The function of turbine tip-speed ratio (λ) and blade pitch angle (β). Power coefficient (C_P) of wind turbine represents the efficiency of converting kinetic energy to mechanical energy. Theatrically the maximum efficiency (C_P) of wind turbines is 0.593 (59.3%), that is known as Bentz limit.

(4) Wind Turbines Performance and Effect Parameters

- **Tip-Speed Ratio:** The tip-speed ratio is a crucial parameter, that can affect wind turbine efficiency. The mathematical expression can be:

$$\lambda = \frac{\omega\ .\ R}{v} \quad (4.12)$$

Where,

$\omega = Angular\ velocity\ of\ wind\ turbine\ rotor\ [rad/s]$

$R = Radius\ of\ rotor\ [m]$

$v = Wind\ speed\ [m/s]$

A wind turbine operates efficiently with the optimal range of λ, where power coefficient (C_P) can reach to maximum.

- **Power Coefficient:** The power coefficient represent is to understand the efficiency of wind turbines, which varies with tip speed ratio. In practical scenario, wind turbines can perform with the C_P values of 0.3 (30%) to 0.5 (50%).
- **Cut-in Wind Speed:** To generate wind power, the minimum speed of turbines should be 3 m/s to 4 m/s (meter per second).
- **Cut-off Wind Speed:** To mitigate the over speed damage of wind turbines, the maximum wind speed considers typically around 25 m/s (meter per second).
- **Rated Wind Speed:** To get the maximum power from wind turbines, the wind speed limit usually around 12 m/s to 15 m/s (meter per second).

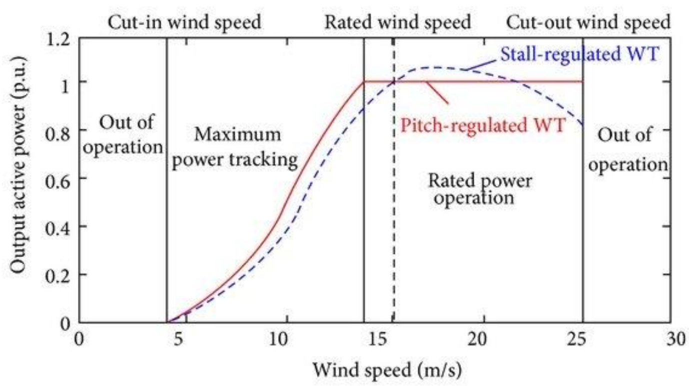

Figure 4.5: Power curve of wind turbine [90]

The mathematical equation of wind turbine power curve is given below:

$$P(V) = \begin{cases} 0 & for\ V < V_{cut\_in} \\ P_{rated} \cdot \left(\frac{V}{V_{rated}}\right)^3 & for\ V_{cut\_in} \leq V \leq V_{rated} \\ P_{rated} & for\ V_{rated} \leq V \leq V_{cut\_off} \\ 0 & for\ V > V_{cut\_off} \end{cases} \tag{4.13}$$

Where,

$P(V) = Wind\ turbine\ power\ output\ [W]$

$P_{rated} = Wind\ trubine\ rated\ power\ output\ [W]$

$V_{cut\_in} = Wind\ turbine\ cut - in\ wind\ speed\ [m/s]$

$V_{rated} = Wind\ turbine\ rated\ wind\ speed\ [m/s]$

$V_{cut\_off} = Wind\ turbine\ cut - off\ wind\ speed\ [m/s]$

(5) Electrical Power Output of Wind Turbines

After getting the mechanical power by the wind turbine, its converter into electrical power by using the generator. The mathematical expression for electrical power output as:

$$P_{elec} = P_{wind} \cdot \eta_{gen} \tag{4.14}$$

Where,

$P_{elec} = Wind\ turbine\ electrical\ power\ output\ [W]$

$P_{wind} = Wind\ trubine\ output\ [W]$

$\eta_{gen} = Generator\ efficiency\ [m/s]$

For example,

Considering a wind turbine with air density ρ =1.25 kg/m^3, wind speed v=10 m/s, rotor radius R=50m, and power coefficient C_P=0.45.

The wind power (mechanical),

$$P_{wind} = \frac{1}{2}.(1.25).\pi.(50)^2.(10)^3.(0.45) = 2.21 \text{ MW}$$

Electrical power generation with the generator efficiency of 95%,

$$P_{elec} = 2.21\ .\ (0.95) = 2.0995\ MW$$

(6) Energy Storage (Battery) System Modeling

The battery energy storage system (ESS) is an electrochemical device, that can store energy either from AC source or DC source. It is one of the key components for hybrid microgrid systems. Battery storage systems are especially essential, to meet the energy demand of loads, when renewable energy is insufficient. The state of charge (SoC) is a vital metric to manage the battery, which represents battery capacity (Ah) at any given time [91]. Mathematically, SoC modeling refers to dynamic behavior of batter systems during discharging and charging cycles. The equation managing the SoC by integration with battery current over time, and connection with total battery capacity. The equation expresses as:

$$SoC(t) = SoC(t_0) + \frac{1}{C_{rated}}\int_{t_0}^{t} I(t)dt$$

$$= SoC(t_0) + \frac{1}{C_{rated}}\int_{t_0}^{t} (I_b - I_{loss})dt \tag{4.15}$$

Where,

$SoC(t) = State\ of\ charge\ at\ any\ given\ time\ t$

$SoC(t_0) = Initial\ state\ of\ charge\ at\ time\ t_0$

$I(t) = Charging\ and\ discharging\ current\ of\ battery\ at\ time\ t$

$C_{rated} = Battery\ rated\ capacity\ (Ah)$

$I_b = Battery\ current$

$I_{loss} = Loss\ reaction\ current\ consumed\ by\ battery$

(7) Technical Principle of Battery Storage System Modeling

The two main important parameters of battery storage systems are state of charge (SoC) and depth of discharge (DoD). Those parameters are essential to optimize battery storage performance and monitoring system to enhance the lifetime. These indicators reflect the battery energy levels (charging and discharging), operational efficiency and battery health over the lifecycle [92].

- **Useable Capacity:** The useable capacity refers to the amount of energy left to use or discharge under operating conditions. State of charge (SoC) is a ratio of usable capacity and rated capacity of battery, that is normally provided by manufacturers.

$$SoC = \frac{C_{useabe}}{C_{rated}} \times 100\% \tag{4.16}$$

- **Maximum Capacity**: A fully charged battery has a maximum usable capacity, that may not be same as rated capacity due to several factors such as aging, temperature, internal resistance, and chemical effects. To measure the battery degradation state of health (SoH) indicator can be used:

$$SoH = \frac{C_{max}}{C_{rated}} \times 100\% \tag{4.17}$$

- **Depth of Discharge**: This is the indicator which represents the percentage of battery capacity that has been discharged compared to rated capacity. The mathematical expression as:

$$DoD = \frac{C_{discharge}}{C_{rated}} \times 100\% \tag{4.18}$$

- **Calculation of DoD:** The change of DoD within the operational period (τ), that can be determined by integrating battery system current over the time. The mathematical expression as:

$$\Delta DoD = \frac{1}{C_{rated}} \int_0^{\tau} I_b \, dt \tag{4.19}$$

The I_b is positive when batter is charging and negative when discharging, also it represents cumulative energy flow within the battery system.

- **Efficiency Consideration:** While battery experiences changing and discharging, it will reduce efficiency due to several losses. To calculate DoD, operating efficiency must be considered, where charging and discharging efficiency are developed to calculate accurate DoD. The mathematical expressions as:

$$\Delta DoD = \frac{1}{C_{rated}} \int_0^{\tau} \eta . I_b \, dt \tag{4.20}$$

- **SoC Considering Battery Aging (SoH):** Accurate SoC calculations is crucial to identify battery health or aging. Battery SoC incorporates with SoH that adjust of real maximum capacity. The mathematical expression as:

$$SoC = \left(\frac{C_{max} - C_{discharge}}{C_{rated}}\right) \times 100\% \tag{4.21}$$

All those battery parameters allow precise real time monitoring and performance, which enhances efficiency.

(8) CO_2 Emission and Efficiency Metrics

Diesel generators are consumed fossil fuels, and their produce emissions are proportional to fuel burns. The emission of carbon dioxide (CO_2) can be calculated by the emission factors [20]. The mathematical expression as:

$$E_{CO_2} = m_{fuel} \, . EF_{CO_2} \tag{4.24}$$

Where,

$E_{CO_2} = Total\ CO_2\ emission\ (kg)$

$m_{fuel} = mass\ of\ fuel\ (kg)$

$EF_{CO_2} = CO_2\ emission\ factor\ (kg)$

- Efficiency: It's a crucial parameter for diesel-based generator performance analysis. The overall efficiency of diesel generators, including electrical and thermal can express as:

$$\eta_{DG} = \frac{P_{DG}}{m_{fuel} \, . \, LHV} \tag{4.25}$$

The efficiency of diesel generators varies with loads, fuel quantity and operating conditions. Hybrid microgrid can be optimized by the model of diesel generators efficiency and reduce the fossil fuel consumption and carbon emissions.

Chapter 5

Results and Discussion

5.1 Introduction

5.1.1 Brief Overview

This chapter represents the results and discussions of the research conducted on hybrid microgrid systems. Hybrid microgrid system (HMG's) plays a vital role in the modern energy system transition by integrating diverse renewable energy sources including solar PV system, wind energy, geothermal, ocean energy, and hydro energy along with multiple energy storage systems and traditional generators [93]. All these different combinations of microgrid offer multiple advantages, along with grid stability, uninterrupted power supply, even in off-grid areas, where conventional grid infrastructure may not be available.

Hybrid microgrid system design and optimization has several challenges. The most important challenges are the fluctuation and intermittency of renewable energy generation sources. Solar photovoltaic and wind energy can vary significantly with the weather conditions, which make energy forecasting more complex along with managing the energy output. On the other hand, optimizing the hybrid microgrid system performance requires robust control strategies to ensure reliable energy supply under extreme weather and load conditions [94]. Another significant challenge is to integrate diverse energy storage systems to balance energy demand and supply within the hybrid microgrid areas.

5.1.2 Objectives:

The main objectives of this Chapter are to:

- **Evaluate ML Model Forecasting Technique:** Using machine learning model of Long Short-Term Memory (LSTM), load demand and renewable energy output can predict accurately. The main objective is to identify accurate forecasting of energy demand, solar irradiance, temperature, and wind speed.
- **Optimize Renewable Energy (PV) Generation Using MPPT Algorithm:** To optimize the renewable energy generation MPPT algorithm is very essential. The objective is to make the performance comparison with four different MPPT techniques such as Perturb and Observe (P&O), Predictive Control Method (PCM), Fuzzy Logic Control (FLC) and Artificial Neural Networks (ANN).

- **MATLAB Simulink Model Development:** Develop a hybrid microgrid system in MATLAB Simulink environment with all the required components and simulate the behavior under extreme operating conditions.

5.1.3 Project Site Description:

This research specifically focuses on develop a hybrid microgrid system for the location of Ericeira (Lat: 38.967675, Long: -9.407825), Mafra, Lisboa, Portugal. One of the primary reasons to choose the location is available hourly energy consumption (1 year) data from E-REDES [95]. E-REDES is the electricity distribution network operator in Portugal. Recently they started provides hourly and monthly energy consumption data by various regions in Portugal. For accurate energy demand forecasting real data is very essential, which is pivotal for modeling and simulation of hybrid microgrid system.

Figure 5.1: Location of the project site (Lat: 38.967675, Long: -9.407825)

Ericeira is a touristic and costal area, which makes it the perfect location to install hybrid microgrid system due to available renewable resources. This study is driven by enhancing sustainable and reliable energy supply and setting a benchmark for similar projects in other locations, which contribute more resilience and greener energy future.

5.2 Energy Demand Forecasting Results and Discussion

5.2.1 Energy Demand Forecasting

The energy demand forecasting was carried out by Long Short-Term memory (LSTM) machine learning model. To select of LSTM model for its accuracy in time series analysis. The forecasting model was trained using 1 year (November 2022 to November 2023) of E-REDES dataset with the features of day (hours), daily pattern, and seasonal and yearly demand variations. LSTM model has the capability to learn long and short-term dependencies, which made it perfect choice for capturing extreme fluctuations and trends of energy demand.

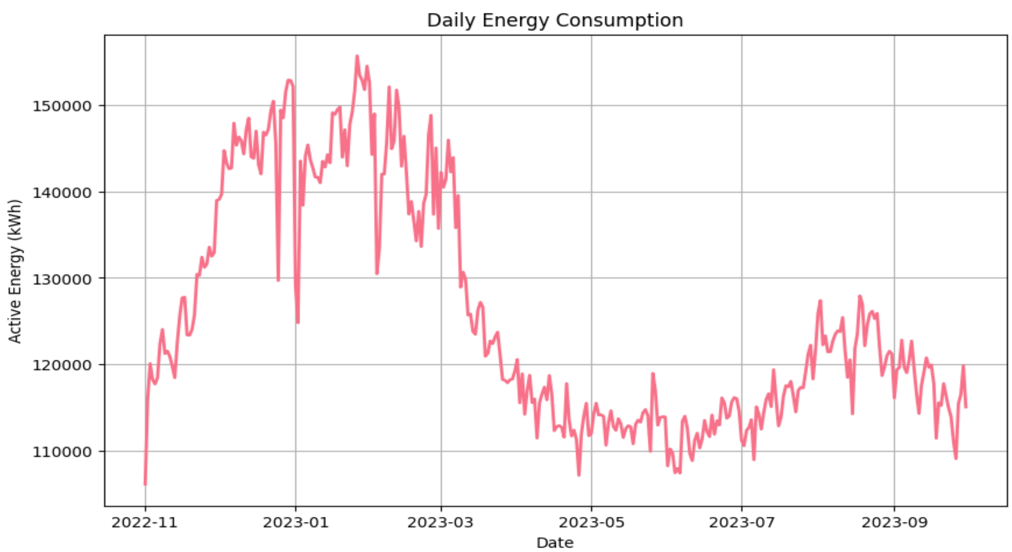

Figure 5.2: Daily energy consumption patterns of the location (Ericeira)

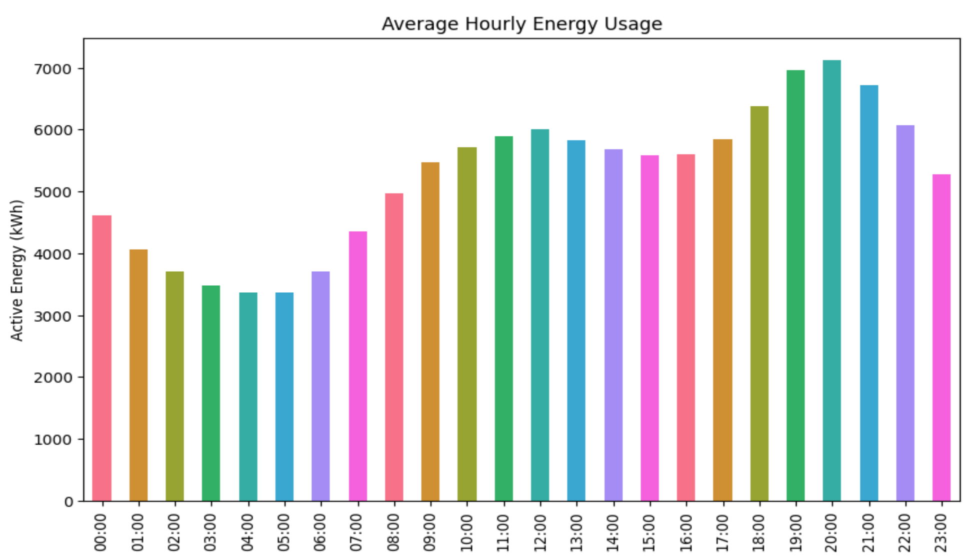

Figure 5.3: Average hourly energy demand forecasting by a day

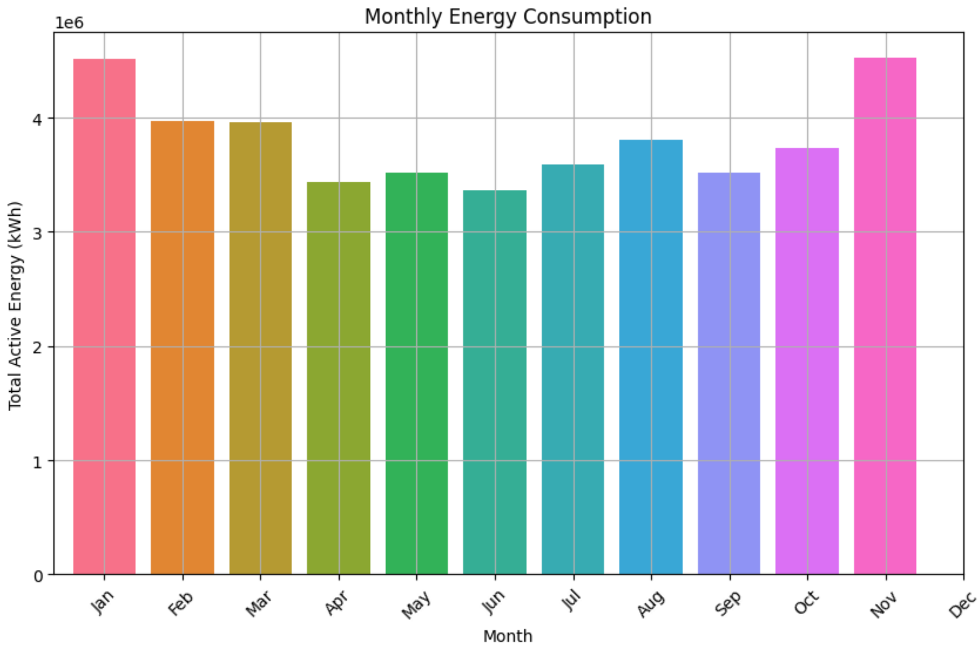

Figure 5.4: Average monthly energy consumption patterns of the location

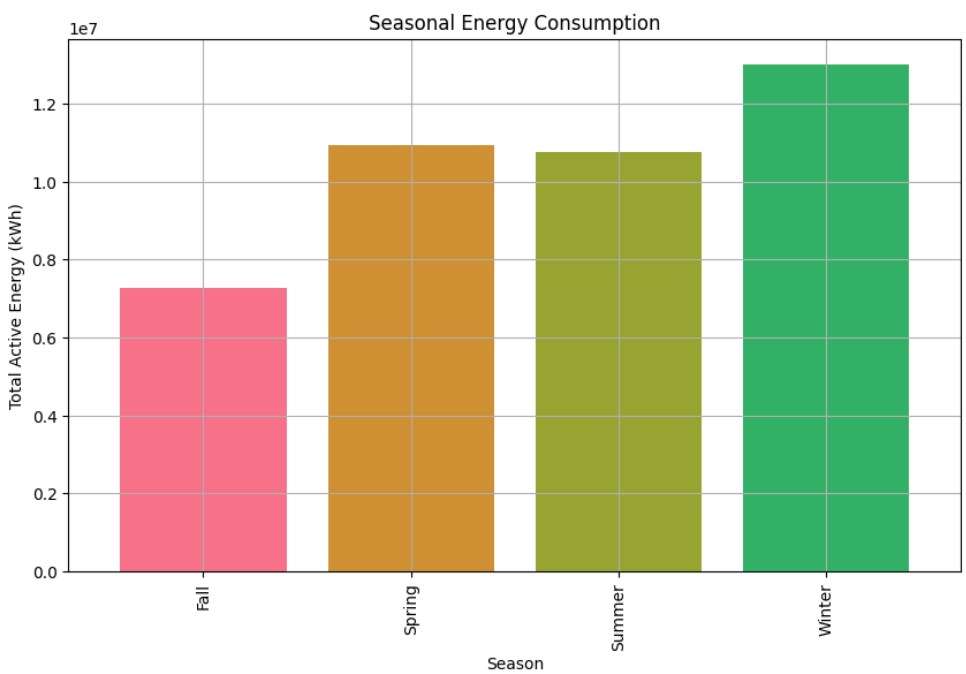

Figure 5.5: Seasonally energy demand variation patterns of the location

Energy Demand of Ericeira Area		Required Capacity (kWh)
Average hourly energy demand		5.24
Average peak hourly demand		6.71
Average daily demand		125.81
Average peak daily demand		155.72
Average monthly demand		3820.09
Average seasonal demand variation	Fall	7266.69
	Spring	10939.50
	Summer	10779.29
	Winter	13035.54
Average seasonal demand		10505.25
Annual demand		42021.02
Load factor		0.68

Table 5.1: Required energy demand capacity analysis for the area of Ericeira, Lisboa, Portugal

Hour	Hourly Energy Demand (Wh)
0	4350.21
1	3878.48
2	3583.67
3	3400.53
4	3361.22
5	3543.92
6	4029.09
7	4679.04
8	5240.54
9	5615.67
10	5817.82
11	5959.67
12	5928.30
13	5744.26
14	5623.50
15	5560.78
16	5657.99
17	6020.58
18	6679.50
19	7161.38
20	6963.19
21	6382.00
22	5666.94
23	4966.40

Table 5.2: Hourly energy demand data

5.2.2 Methodology of Energy Demand Forecasting

The methodology of energy demand forecasting for hybrid microgrid systems (HMG's) employing Long Short-Term Memory (LSTM) machine learning model. The LSTM model comprises with several steps, each contributes to the development of a precise energy demand prediction system. The steps include relevant data collection and processing, according to machine learning model selection and architecture design. Once model architecture is selected, then the training process starts. Model evaluation and performance are constructed utilizing the metrics of MAE, RMSE and R^2, which ensure accurate prediction results and reliability.

This methodology can be more understandable using the flowchart in figure 5.6. To visualize the representation of the process from the stating of data collection to model architecture, selection, and evaluation. The flowchart provides all the steps of the methodology, which ensures the entire required process for energy demand prediction. The flowchart is given below:

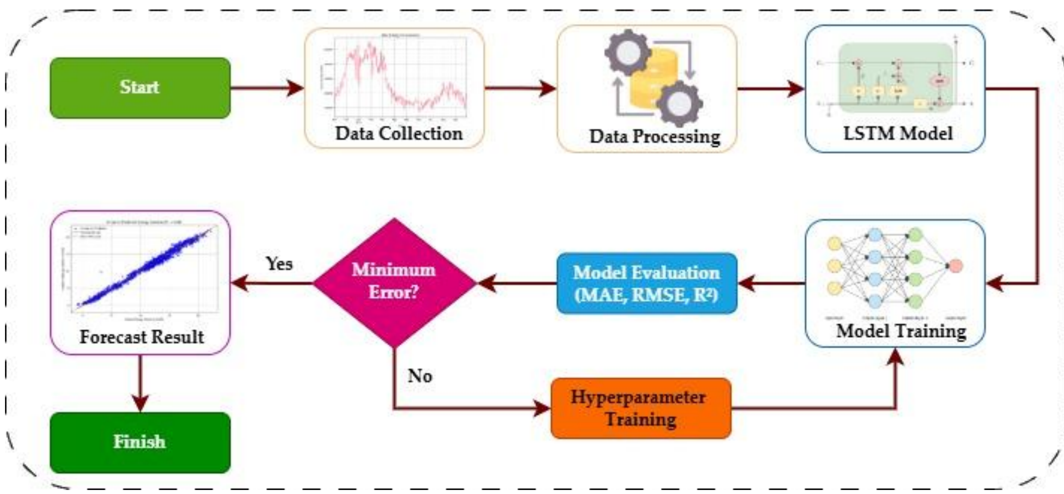

Figure 5.6: Energy forecasting flow chart

5.2.3 Energy Demand Forecasting Evaluation and Results

The LSTM model for energy forecasting was developed and evaluated considering the important key performance metrics, such as

- **Mean Absolute Error (MAE):** 0.44 kWh
- **Root Mean Squared Error (RMSE):** 0.59 kWh
- **Coefficient of Determination (R^2) Score:** 0.99

These results of the metrics indicate low mean absolute and root mean squared error and high coefficient of determination, which suggest that the model is perfectly fitted within actual and predicted energy demand dataset. The lower value of mean absolute error (MAE) refers to high precision and it suggests that the prediction model is very close to the actual values. A small root mean squared error (RMSE) which means that the model is well fitted. It validates that the model has the capability to handle the data fluctuation effectively. For the coefficient of determination (R^2) indicates 99% of variance of actual data. The R^2 value is very close to 1, which means that model is excellent, which capture almost all the patterns in dataset.

A. Visualization of the Forecasting Results

- **Model Training and Validation Loss:** To find out the best fit for LSTM model and enhance the evaluation metrics, it must be trained according to dataset. Figure 5.7 shows the model is well fitted at 33 epoch, where training and validation loss is minimum. On the other hand, more than 33 epoch the model will be overfitted (The code is written such a way, so that it stops the training when the training and validation loss is minimum), that increase the training and validation losses and minimizes the overall model performance.

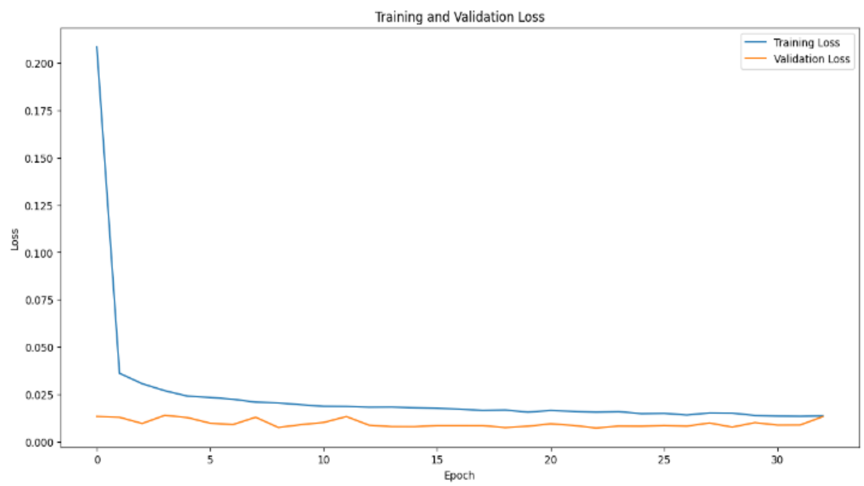

Figure 5.7: LSTM model training and validation loss

- **Performance Metrics Heatmap:** The heatmap represents the quick comparison between different performance metrics and models, that shows which model and metrics is best fitted. The values and color gradient helps to recognize metrics performance.

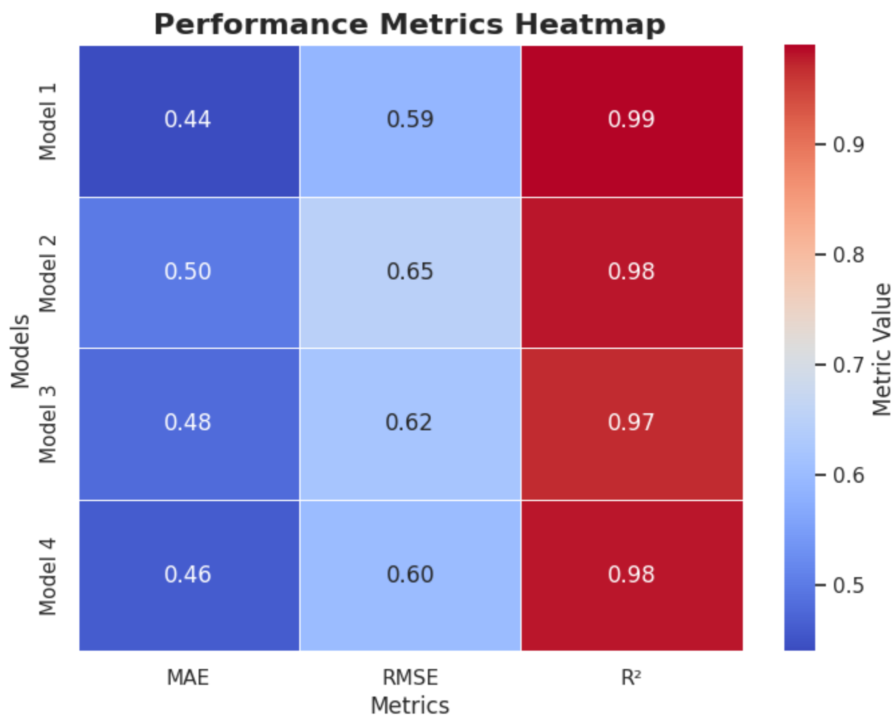

Figure 5.8: Performance metrics heatmap for MAE, RMSE and R^2

- **Coefficient of Determination (R^2)**: The comparison among actual v/s forecasted energy demand for coefficient of determination (R^2) metric, with the value of 0.99 (99%) demonstrate excellent energy demand forecasting.

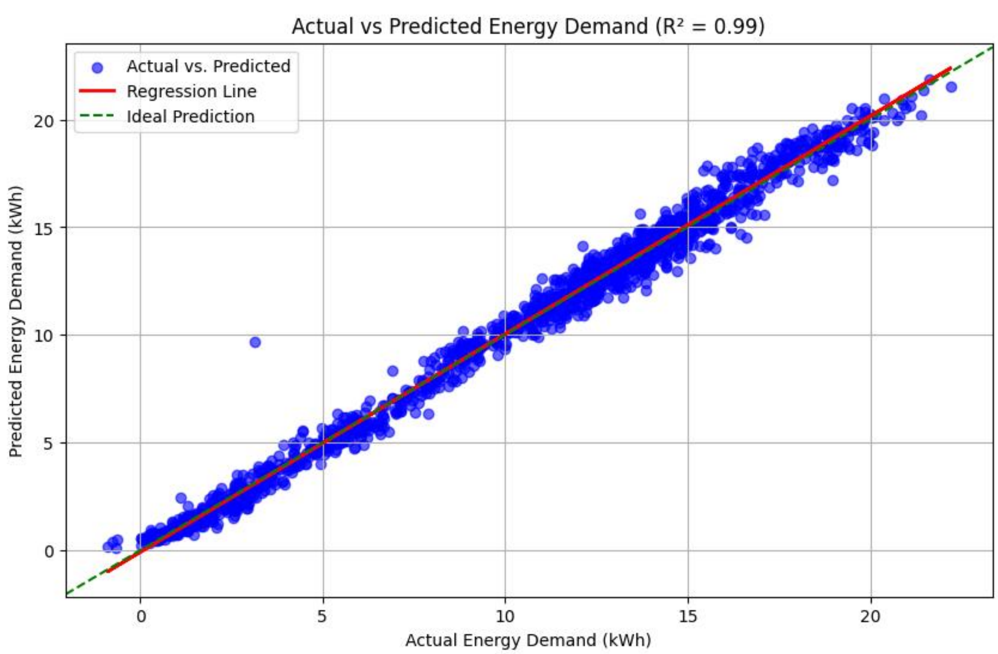

Figure 5.9: Actual vs prediction energy demand for R^2 metrics

- **Model Fitting**: The figure 5.10 indicates the LSTM model is well fitted with the historical (hourly) energy demand dataset. The model is perfectly captured all the variable patterns over a long period.

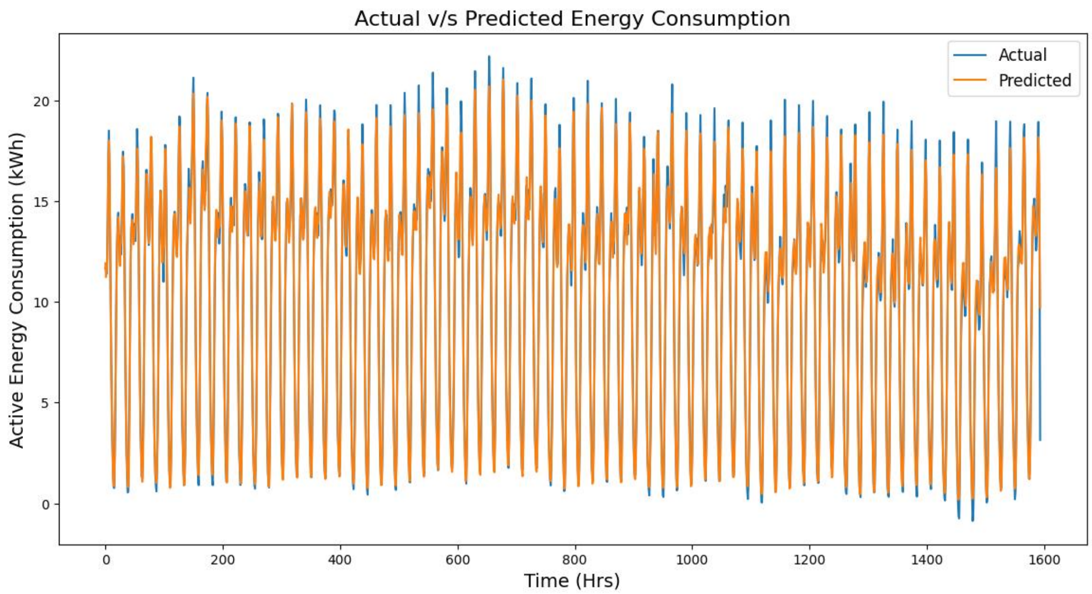

Figure 5.10: Model fitting for actual vs predicted pattern

- **Future Predictions**: After completing the LSTM model training, testing and evaluation. It will be used for future energy demand prediction. So that, we can analyze how much energy is required in future for the project location. According to figure 5.11, it shows future energy demand of the location. This valuable insight helps to plan and optimize hybrid microgrid system sizing, installation, maintenance, and minimize the project overall costs.

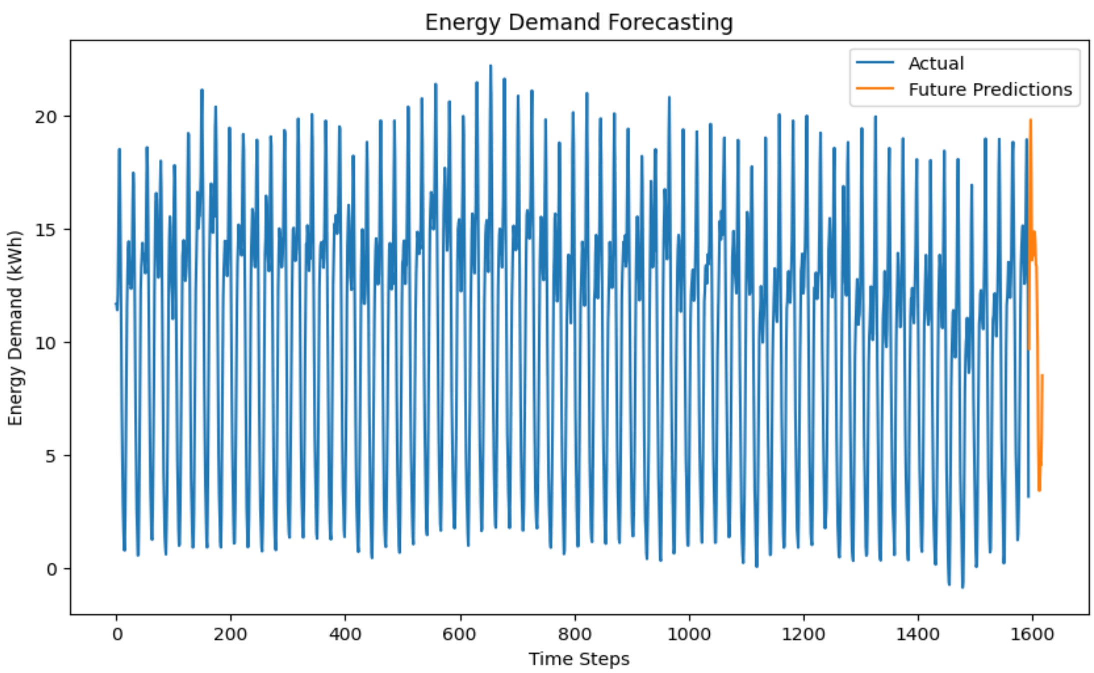

Figure 5.11: Energy demand forecasting of actual and future predictions

5.2.4 Discussion of Energy Demand Forecasting

- **Accuracy and Reliability**: The energy demand forecasting model accuracy can be evaluated utilizing the comparison of actual energy consumption with predicted energy demand over the time. According to the prediction performance metrics, it is obvious that the long short-term memory (LSTM) model demonstrates high accuracy of prediction. Nevertheless, in extreme weather conditions can increase unexpected energy demand, which reduces accuracy of energy demand forecasting models. In this prediction model accuracy is very high, which enhances the reliability of energy demand forecasting for hybrid microgrid system.
- **Challenges and Improvement**: Although the LSTM forecasting model offers high forecasting accuracy, some challenges remain, like handling abnormal weather events, and very short-term energy demand fluctuations. For future improvements can be included an advanced hybrid model, with incorporating multiple features that can handle extreme conditions and short-term fluctuations.

5.3 RE Resource Forecasting Results and Discussion

5.3.1 RE Resource Forecasting

Renewable energy resource forecasting is essential for optimizing the hybrid microgrid system. Solar irradiance, temperature, and wind speed data have been analyzed to calculate optimal renewable energy generation at the location. To predict the optimal renewable energy resource, the machine learning model was carried out by Long Short-Term memory (LSTM). The ML model was trained using 18 years of PVGIS [96] dataset with the features of time of day (hours), daily pattern, seasonal and yearly generation variations. PVGIS is a reliable and open-source data for European countries, that includes solar irradiance (GHI), ambient temperature and wind speed. LSTM model has the capability to learn long and short-term dependencies, which made it perfect choice for capturing extreme fluctuations and trends.

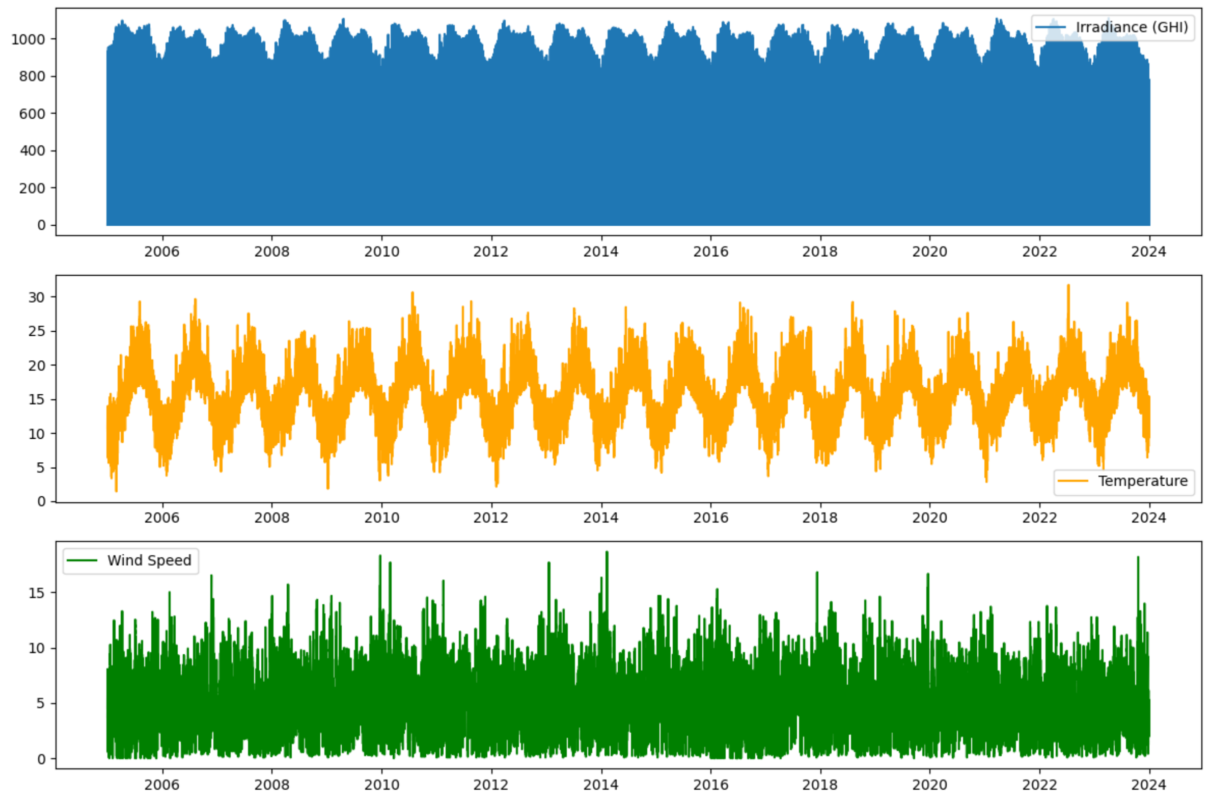

Figure 5.12: 19 years of irradiance, temperature, and wind speed at the project location

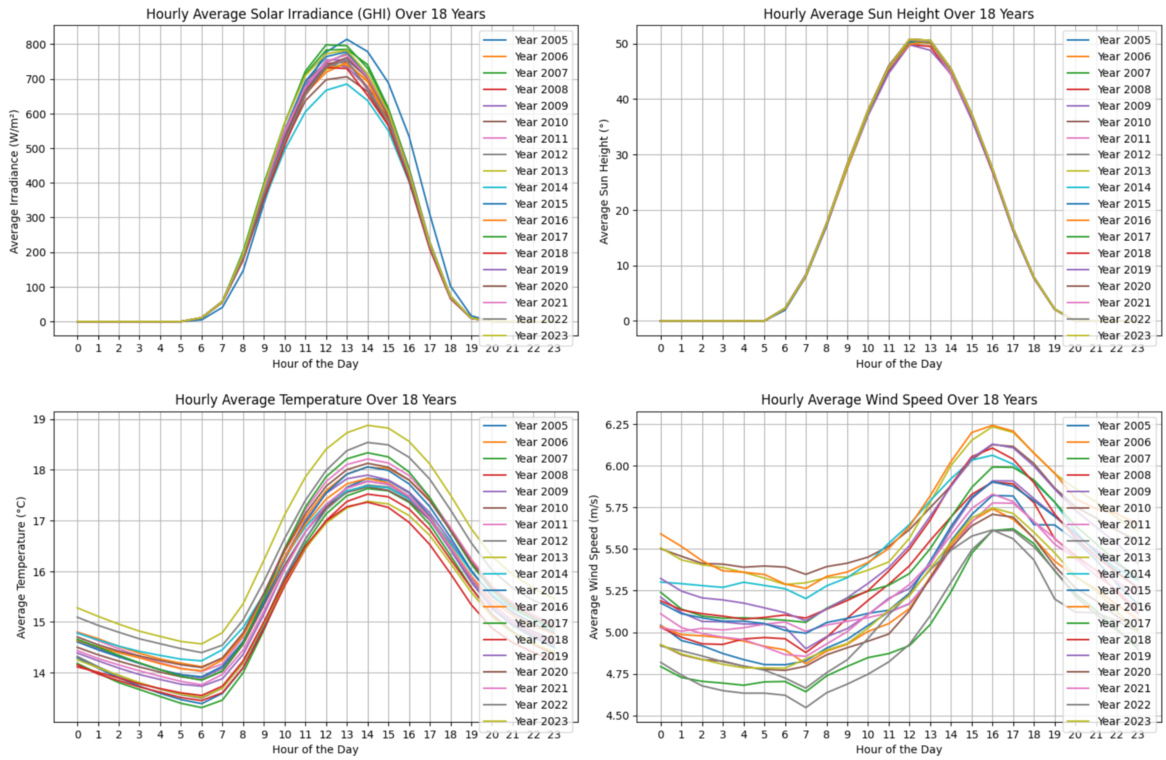

Figure 5.13: Hourly average irradiance, temperature, sun height and wind speed distribution

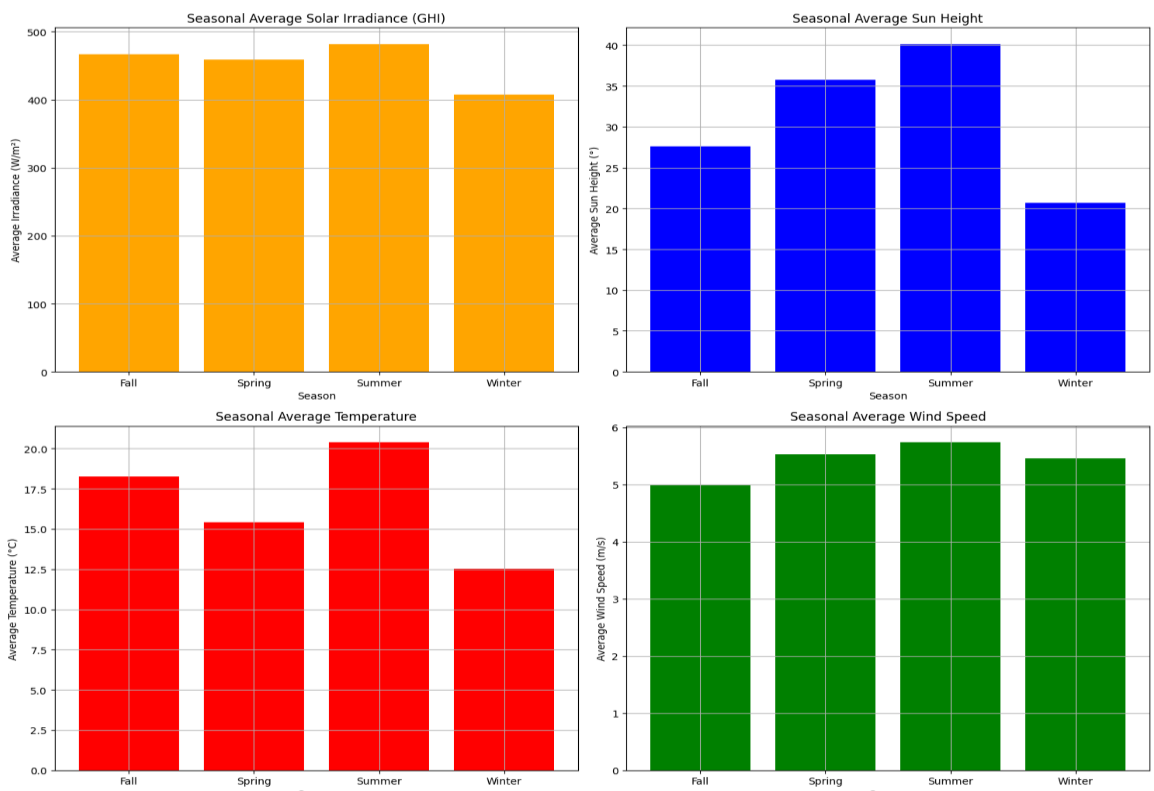

Figure 5.14: Seasonal patterns of irradiance, temperature, sun height and wind speed

- **Average hourly patterns of solar irradiance**

The hourly average global horizontal solar irradiance (W/m^2) represents a clear pattern of daily irradiance at the location. According to the analysis (Table 5.3), the sun rises at 6 o'clock in the morning. At morning and evening the sun irradiance is minimum. The peak solar irradiance occurs within 12 to 1 PM. According to the data the maximum solar irradiance recorded at 1 PM (755.23 W/m^2). At morning solar irradiance is gradually increasing and after peak hour irradiance is gradually degreases. After 6 PM it is considered to be night. This daily solar irradiance pattern refers to be normal solar cycle.

Hours	Hourly Average Solar Irradiance (W/m^2)
0	0.00
1	0.00
2	0.00
3	0.00
4	0.00
5	0.00
6	10.61
7	56.27
8	188.20
9	371.93
10	536.58
11	671.83
12	743.28
13	755.23
14	695.30
15	594.19
16	431.04
17	223.49
18	72.19
19	10.18
20	0.00
21	0.00
22	0.00
23	0.00

Table 3.3: Daily solar irradiance patterns at the location

- **Average hourly patterns of ambient temperatures**

The hourly average ambient temperature (°C) refers to a pattern of daily temperature at the project location. According to the EDA analysis (Table 5.4), the lowest temperature observes at morning hours (within 05-06 AM) and then gradually temperature increases as the sun rises. The peak ambient temperature occurs around 2 to 3 PM. According to analysis the maximum temperature recorded was at 2 PM (17.91). The morning temperature gradually increases and after peak hour the temperature gradually decreases in evening. The normal temperature pattern table given below:

Hours	Hourly Average Ambient Temperature (°C)
0	14.56
1	14.40
2	14.26
3	14.13
4	14.01
5	13.92
6	13.85
7	14.04
8	14.54
9	15.33
10	16.18
11	16.91
12	17.45
13	17.78
14	17.91
15	17.85
16	17.60
17	17.17
18	16.59
19	15.98
20	15.46
21	15.14
22	14.91
23	14.72

Table 5.4: Daily ambient temperature patterns at the location

- **Average hourly patterns of wind speed**

The daily (hourly) average variation of wind speed (m/s) exhibits a pattern led by atmospheric dynamics and sun heating at the project location. During the morning between 6 to 7 AM, wind speed is lowest for minimal turbulence. As the sun rises, solar intensity also increases surface heating and promotes atmospheric mixing. Due to mixing wind speed also increases steadily. The peak wind speed is at approximately around 3 to 5 PM. At night when temperature drops, atmospheric stability also enhances and wind speed drops gradually. Wind speed behavior understanding is crucial to optimize the wind energy generation. The normal temperature pattern table given below:

Hours	Hourly Average Wind Speed (m/s)
0	6.17
1	6.10
2	6.05
3	6.04
4	6.02
5	6.01
6	5.99
7	5.94
8	6.02
9	6.08
10	6.17
11	6.25
12	6.37
13	6.56
14	6.79
15	6.97
16	7.08
17	7.04
18	6.90
19	6.74
20	6.60
21	6.49
22	6.38
23	6.28

Table 5.5: Daily wind speed patterns at the location

- **Correlation Between Irradiance, Temperature, and Wind Speed**

Solar irradiance, ambient temperature, and wind speed demonstrate a dynamic inter relationship due to metrological process. Solar irradiance pattern reaches peak at solar noon (around 12-1 PM). This solar irradiance leads to increases the ambient temperature through thermal inertia of environment. Whereas, wind speed is influenced by the temperature, as the land surface warms, conduction current can be strong and increase the wind speed at noon. Excessive land surface heating can sometime be a reason to reduce wind speed. The correlation of solar irradiance, temperature and wind speed exhibit clear understanding and variations.

Figure 5.15: Correlation heatmap of irradiance, temperature, and wind speed

5.3.2 Methodology of Renewable Energy Resources Forecasting

The renewable energy resources forecasting refers to the systematic methodology, which begins with required data acquisition and preprocessing. Reliable long-term historical data sources are essential for accurate energy generation prediction. The process involves managing missing or error values, eliminating inconsistencies, and normalizing the dataset for consistency. Then feature engineering is performed to extract irradiance, temperature, and wind speed patterns, that include time series variables such as hourly, daily, monthly and seasonal trends.

Once the dataset is ready, LSTM machine learning is considered for solar irradiance, ambient temperature, and wind speed forecasting. The prediction mode is trained using the long-term historical data. Hyperparameters are used to optimize and enhance forecasting accuracy. During this process, cross-validation models are employed to stop overfitting. To test and validate the model performance, several major metrics are considered like, MAE, RMSE, and R^2 are utilized.

After successful training, the LSTM model is deployed for future renewable resources prediction. The objective of renewable resource forecasting is to calculate accurate renewable energy production, optimizing energy storage, demand management, and minimizing the costs. Additionally, renewable energy resource forecasting plays a vital role for grid stability, renewable energy integration, reliability, and grid resilience. The flowchart of renewable energy resource forecasting is given below:

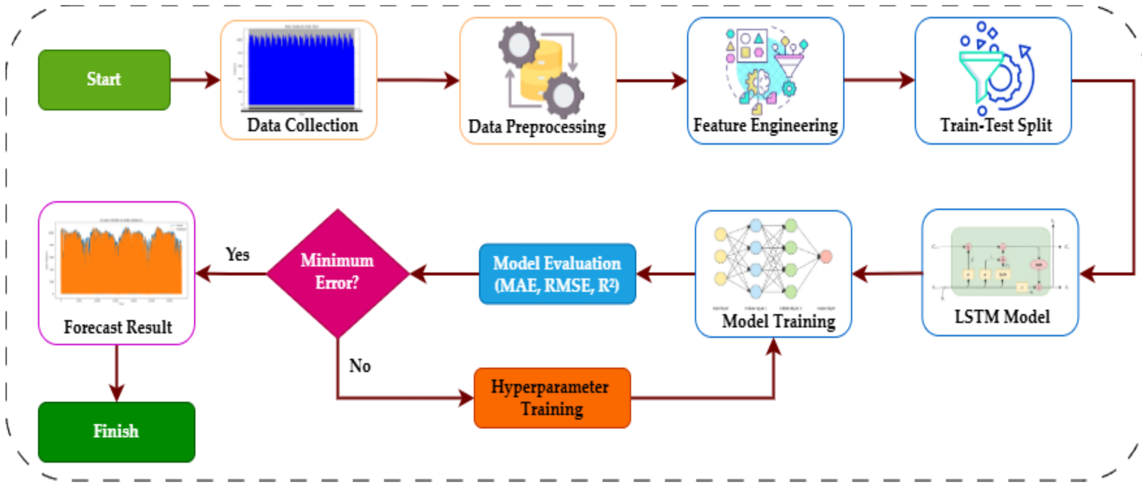

Figure 5.16 Solar irradiance forecasting flow chart

5.3.3 Renewable Energy Resource Evaluation and Forecasting Results

The LSTM model for renewable energy resource forecasting was developed and evaluated utilizing the important key performance metrics of irradiance, temperature and wind speed.

Metrics	Parameters		
	Irradiance (W/m^2)	Temperature (°C)	Wind Speed (m/s)
MAE	0.23	0.18	0.78
RMSE	0.49	0.26	1.14
R^2	0.94	0.99	0.97

Table 5.6: Model performance metrics for renewable energy resource forecasting

These results of the metrics refer to low mean absolute error, and root mean squared error and high coefficient of determination. The result suggests that the model is perfectly fitted among actual and predicted renewable energy resource dataset. The lower values of mean absolute error (MAE) illustrate high precision. They suggest that the prediction model is very close to the actual values. The small root mean squared error (RMSE) means that the model is well fitted. It validates that the model has the capability to handle the resource data fluctuation effectively. For the coefficient of determination (R^2) indicates 94%, 99% and 97% respectively of variance of actual data (Irradiance, temperature, wind speed). The R^2 value is close to 1, that mean model is excellent, which capture almost all the patterns in dataset.

A. Visualization of the Renewable Energy Forecasting Results

- **Model Training and Validation Loss:** To best fit the model and evaluate LSTM, it needs to be trained according to the historical dataset. According to the figure 5.17, the model is well trained, and after 48 epoch training and validation loss is minimum (The code is written such a way, so that it stops the training when the training and validation loss is minimum). More than 48 epoch the model will be overfitted, which increases the training and validation losses and reduces the performance.

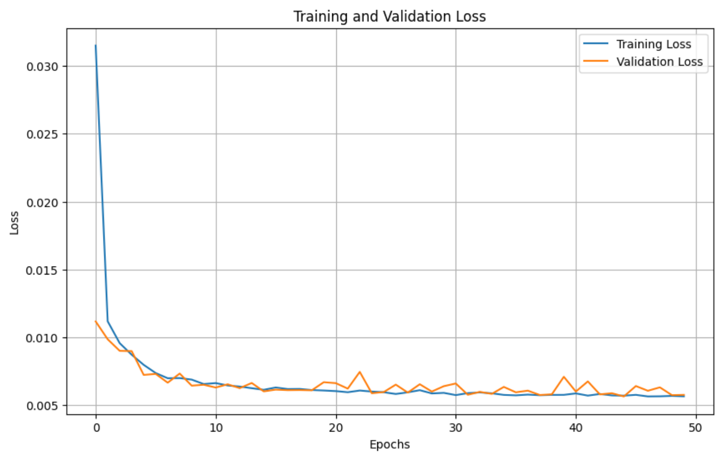

Figure 5.17: Model training and validation loss of renewable energy resources

- **Performance Metrics Heatmap:** Heatmap figure illustrates quick comparison between different performance metrics and parameters. It shows which metrics and parameters are the best fitting to the model. The values and color gradient helps to recognize the model performance.

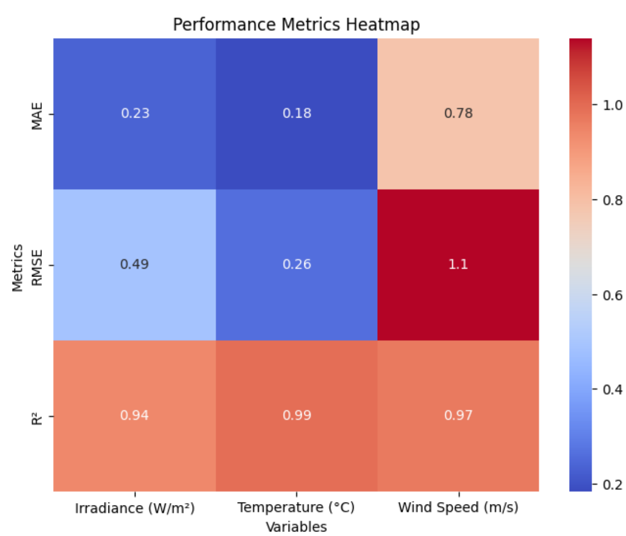

Figure 5.18: Renewable energy resource performance metrics heatmap

- **Coefficient of Determination (R^2)**: Machine learning model accuracy comparison among actual and forecasted renewable energy resource for coefficient of determination (R^2) metric, with the value of solar irradiance 0.94 (94.0%), temperature 0.99 (99.0%), and wind speed 0.97 (97.0%) demonstrate excellent renewable energy resource forecasting. Due to high fluctuation of solar irradiance, its accuracy is less than the other parameters.

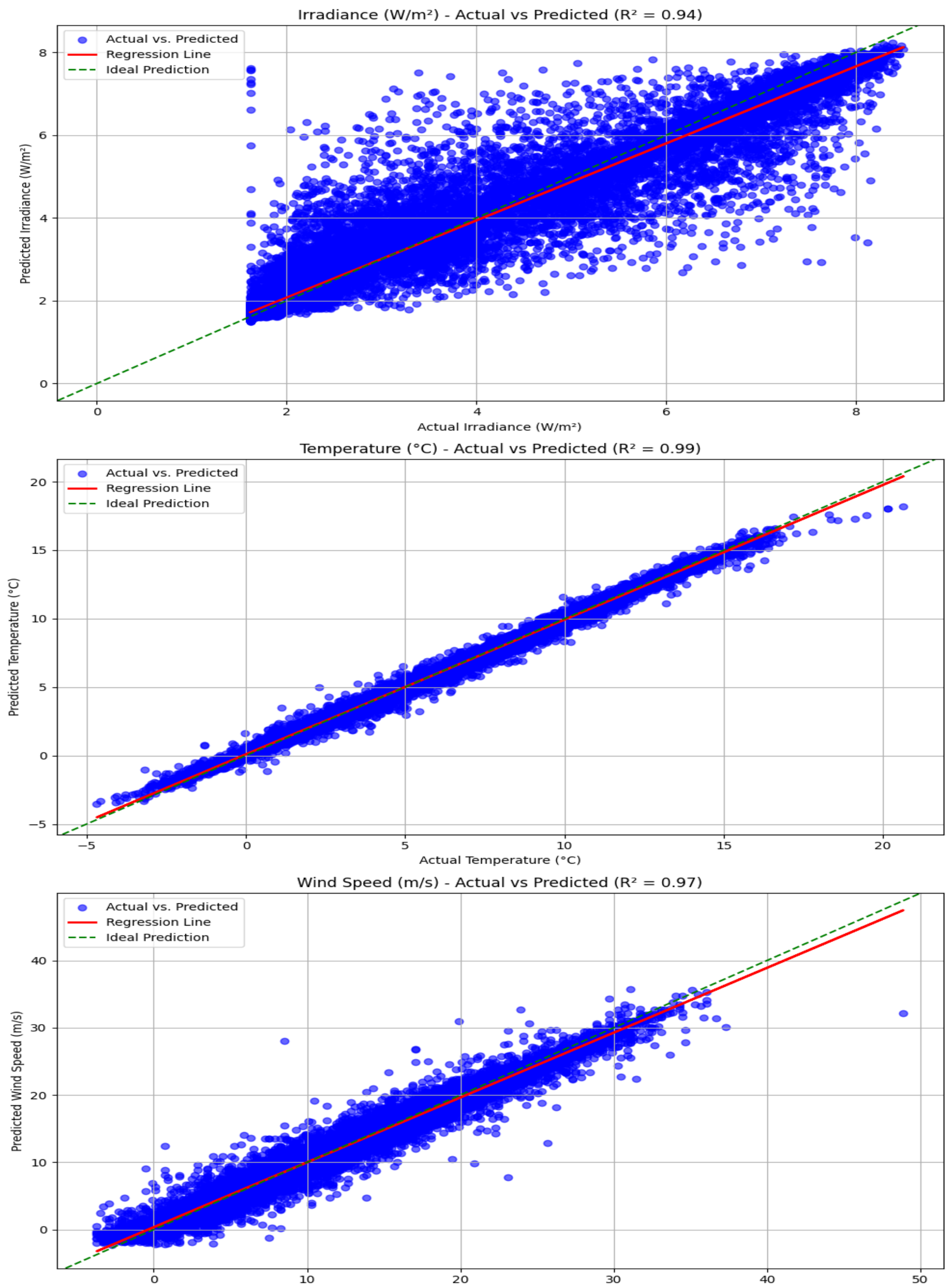

Figure 5.19: Actual vs predicted renewable energy for R^2 metrics

- **Model Fitting:** The LSTM model is well fitted with the historical (hourly) renewable energy resource dataset. It shows the model is perfectly capturing all the parameters patterns over a long period of time.

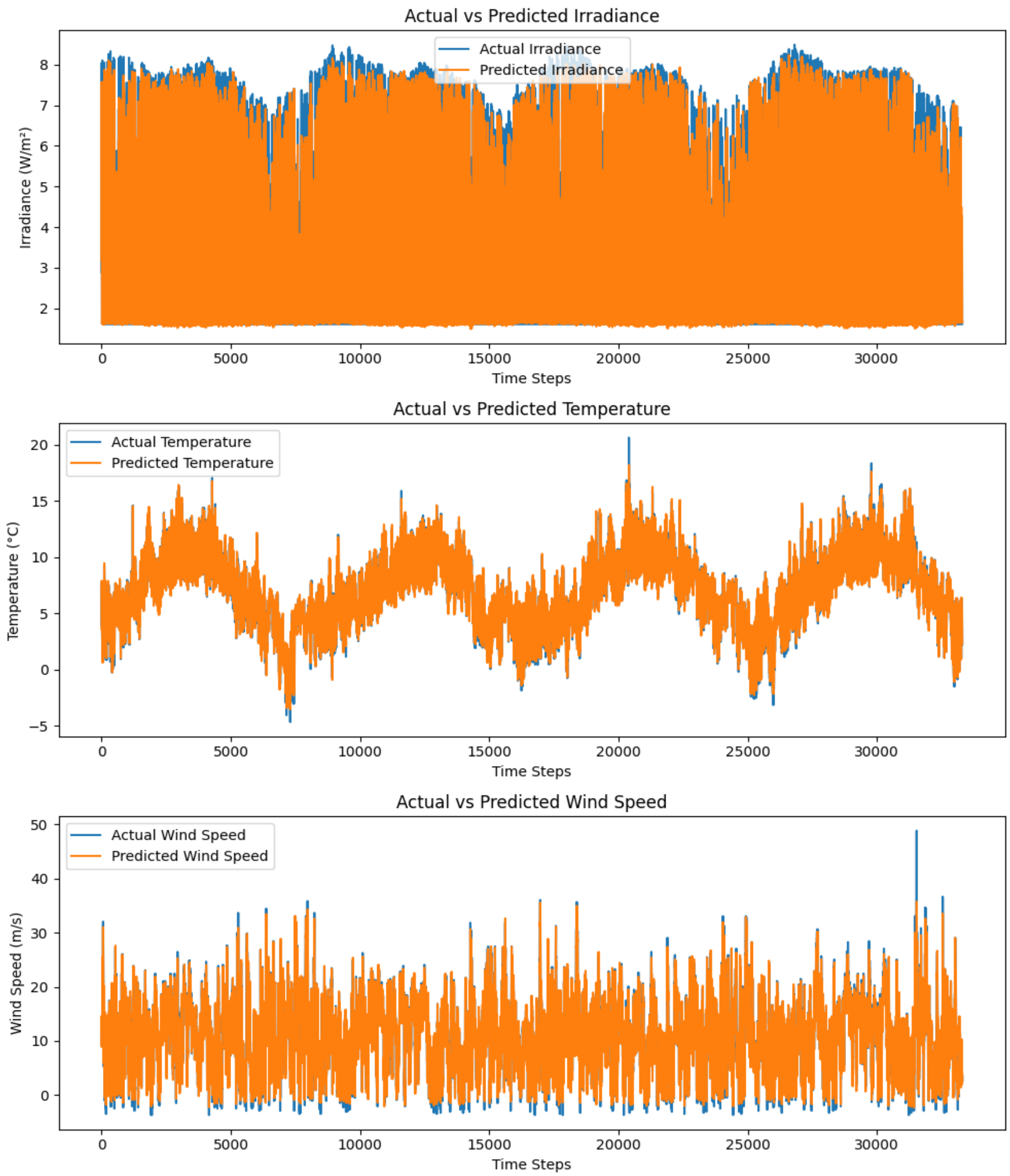

Figure 5.20: Renewable energy resource model fitting for actual vs predicted pattern

- **Future Predictions:** After completing the LSTM model training, testing and evaluation, it needs to be supplied for future renewable energy resource prediction. It helps us to analyze how much renewable energy can be produced in future, from the specific location.

According to figure 2.21, it shows future irradiance, temperature and wind speed predictions of the location. This valuable insight helps to planning and optimization of hybrid microgrid system sizing, installation, and maintenance.

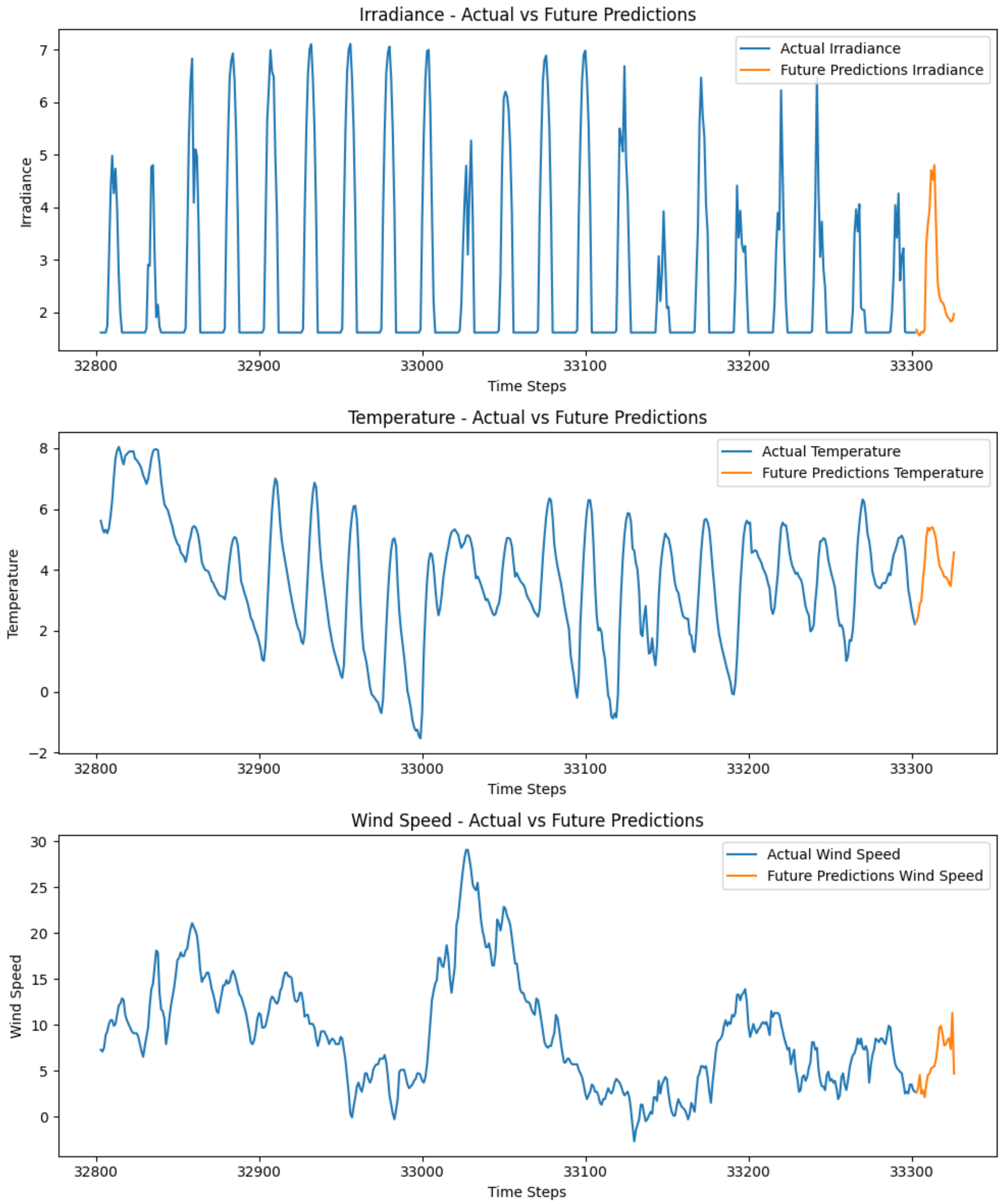

Figure 5.21: Renewable energy resource forecasting of actual and future predictions

5.3.4 Discussion of Renewable Energy Forecasting

The renewable energy resource forecasting provides valuable insights into trends and highlights prediction model strengths and limitations.

- **Accuracy and Reliability**: The renewable energy resource forecasting model accuracy was evaluated compared with the actual historical long term (19 years) renewable energy resources with predicted renewable energy resources. The forecasting model (LSTM) performance metrics indicate how effective the model is to capture daily and seasonal fluctuations of solar irradiance, temperature and wind speed. In extreme weather conditions there can be an increase high in fluctuations of renewable energy resources, that can reduce accuracy of renewable energy resource forecasting. The prediction model demonstrates very high accuracy, which enhances the reliability of renewable energy resource forecasting for hybrid microgrid systems.
- **Challenges and Improvement**: Although the LSTM forecasting model offers high accuracy, still there are some challenges remaining, such as handling abnormal weather events, very short-term irradiance, temperature, and wind speed variations. For future improvements, can be included advanced hybrid models, with incorporating multiple features that can handle extreme conditions and short-term fluctuations. Additionally, integrating real time IoT based system and adaptive machine learning technique can enhance model performance and ability to handle very short-term fluctuations.

5.4 MPPT Algorithms Comparison for Optimal Energy Generation

Maximum Power Point Tracking (MPPT) algorithm is crucial to extract the maximum power from the solar PV modules. In this part the MATLAB/Simulink model would be presented and analyze the simulation results. This analysis makes the comparison between four (4) different MPPT techniques. Those techniques are evaluated using their effectiveness with the metrics of tracking efficiency, power oscillation, convergence speed, and extreme environmental conditions response.

5.4.1 Overview of MATLAB/Simulink Setup:

To observe the behavior of different MPPT techniques, the MATLAB/Simulink model was developed. The simulation test setup incorporates solar PV arrays with varying solar irradiance, and temperature. The specifications of the test setup are given below.

The specifications of the solar PV panel:

Electrical Characteristics	Capacity Values
Maximum power (Pmax)	213.15Wp
Open circuit voltage (Voc)	36.3V

Short circuit current (Isc)	7.84A
Maximum power voltage (Vmp)	29.0V
Maximum power current (Imp)	7.35A
Module efficiency	17.3%
Maximum system voltage	1500V DC (IEC)
Maximum series fuse rating	15A
Temperature Coefficient of (Isc)	+0.057%/C
Temperature Coefficient of (Voc)	-0.286%/C
Temperature Coefficient of (Pmax)	-0.370%/C
Panel Dimension (H/W/D)	1956x992x45 mm

Table 5.7: Datasheet of 213.15Wp solar PV panel

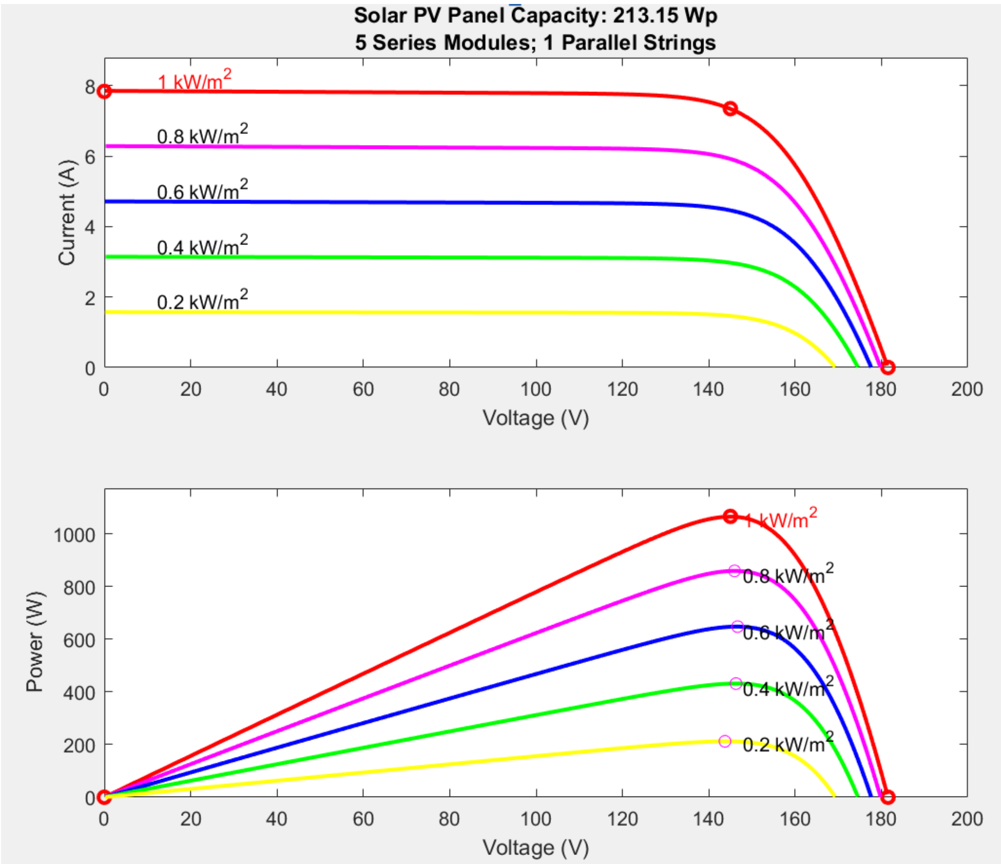

Figure 5.22: IV and PV curve of solar photovoltaic panel

Using the above-mentioned solar PV panels, the MATLAB/Simulink model was developed for MPPT techniques assessment.

- The Maximum Power Point Tracking (MPPT) algorithms are tested:
  1. Perturb & Observe (P&O)
  2. Predictive Control Method (PCM)

3. Fuzzy Logic
4. Artificial Neural Networks (ANN)

5.4.2 MPPT Techniques Performance Assessment:

To find out the performance of different MPPT techniques through measuring the solar PV generated voltage and current [99-100]. The mathematical equation of the MPPT model performance analyzation is given below.

$$\eta_{mppt} = 1 - \frac{|P_{pv} - P_{ideal,stc}|}{P_{ideal,stc}} \tag{5.1}$$

This model was configured in MATLAB/Simulink environment, considering required standard for solar PV panels with variable environmental (irradiance, temperature) conditions. The Similink model block is given below for performance measurement.

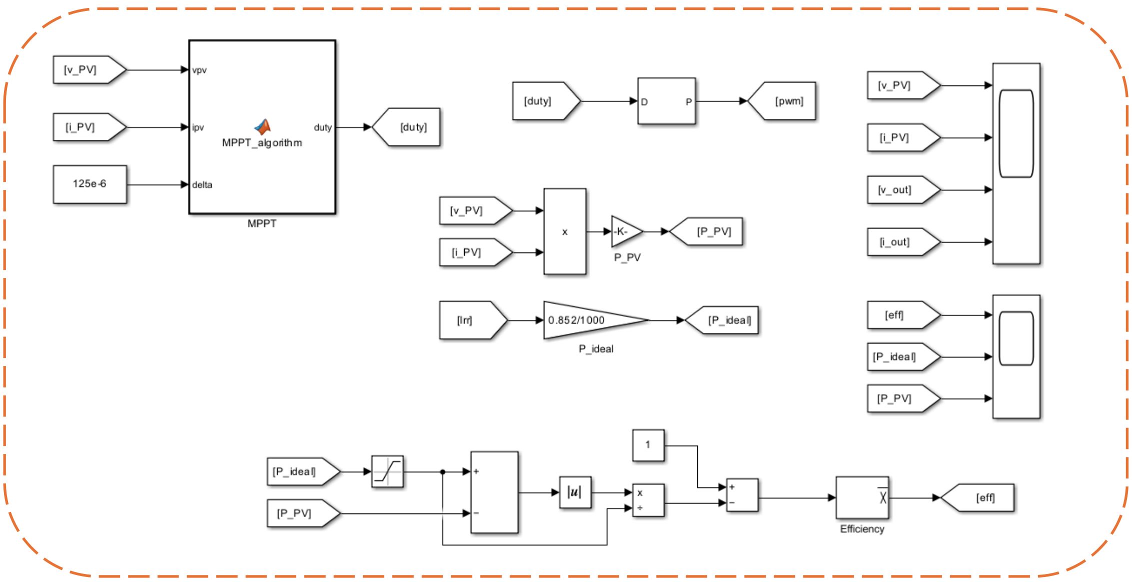

Figure 5.23: MATLAB Simulink diagram to evaluate MPPT efficiency

The efficiency of MPPT techniques for the four different types of algorithms are shown in the figures of 5.25, 5.28, 5.30 and 5.32 respectively.

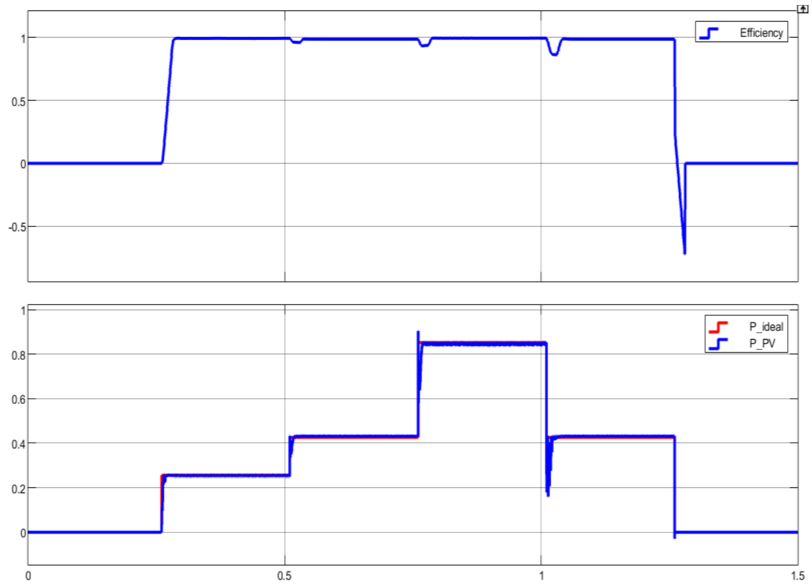

Figure 5.24: Output efficiency curve of MPPT algorithm

The MPPT efficiency figure shows the obtained solar power is very close to ideal solar power. Mean efficiency is close to the unity, when system is steady state. The variable solar irradiance was utilized to evaluate MPPT performance. According to output curve the efficiency is 99%, over 1.5 seconds.

5.4.3 Performance Metrics

To evaluate the performance of each MPPT algorithms, the following metrics are analyzed.

- **Tracking Efficiency (η):** To measure the efficiency of the MPPT algorithm, how it effectively tracks solar PV panels maximum power point (MPP).
- **Response Time (T_r):** After sudden change of solar irradiance and temperature, it will take time to reach the maximum power point.
- **Power Oscillations (ΔP):** Minimum power oscillation refers to smooth operation and enhances the ability of the system.
- **Convergence Speed:** How fast MPPT algorithm convergence to maximum power point (MPP) after disturbance.
- **Computational Complexity:** Processing time requirement and quality of hardware.

Simulation Setup (Experimental):

- MATLAB/Simulink was developed for a 1000 Wp (1.0 kWp) solar photovoltaic system.
- Robust DC-DC boost converters are used as a controlled system for all MPPT techniques.
- **Test conditions**:

Two different conditions are considered to simulate the MPPT algorithms. The first uses a 24-hours continuous dataset (Average irradiance & temperature). The second uses discrete values to analyze the rapidly changing conditions.

- **Solar irradiance**: 200 W/m² → 400 W/m² → 600 W/m² → 800 W/m² → 1000 W/m² → 800 W/m² → 600 W/m² → 400 W/m² → 200 W/m²
- **Ambient temperature**: 20°C → 25°C → 30°C → 35°C → 40°C → 35°C → 30°C → 25°C → 20°C

5.4.4 Perturb & Observe (P&O) MPPT Simulation Setup:

The P&O algorithm is most widely used MPPT technique, because of its simplicity and easy to implement in hardware system. This is also one of the cheapest techniques, although it has oscillation problems near to maximum power point (MPP) that increase power losses. In the simulation, results observe that the P&O technique has a slower response time for irradiance and temperature changes. However, it has several drawbacks but still, it is preferable choice for low cost and simple computational implementation. The MATLAB/Simulink model is given below with the boost converter.

MATLAB/Simulink Model (P&O):

The MATLAB/Simulink model was developed by utilizing extreme environmental conditions. The model included with efficiency measurement blocks to evaluate the performance and power output.

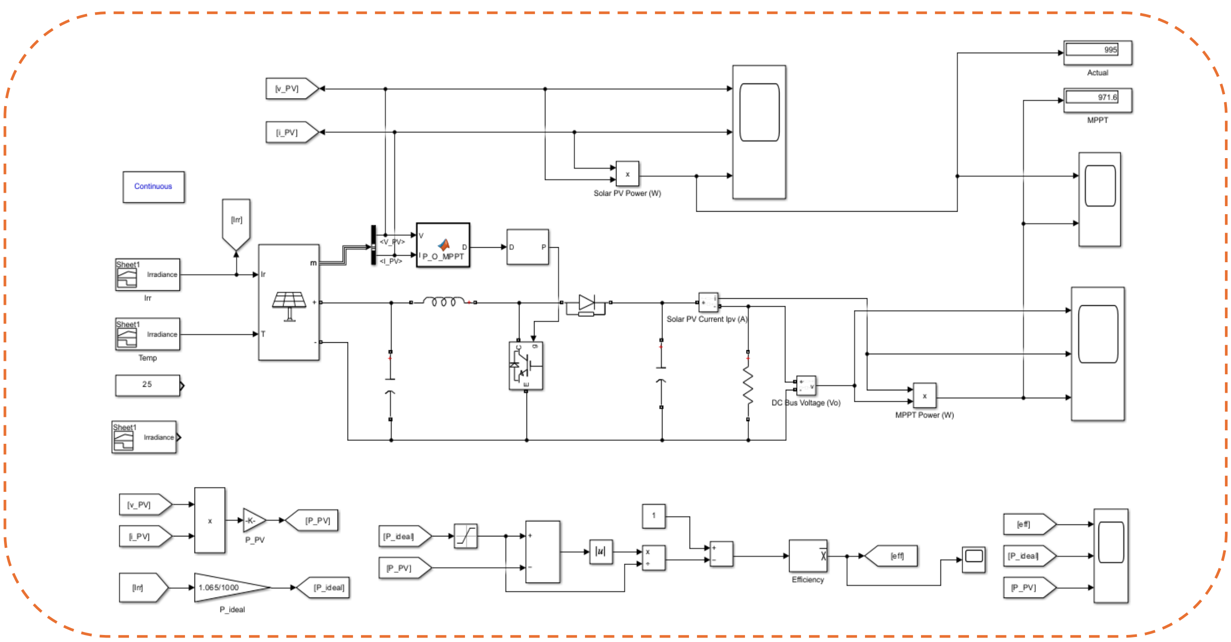

Figure 5.25: MATLAB/Simulink model for P&O MPPT algorithm

Results of P&O Technique (Output Curve):

In the output curve of Perturb and Observe MPPT technique usually exhibits some oscillations near to MPP of solar PV panels. In this operation, algorithm perturbs the duty cycle and observe the power output by tracking MPP.

Figure 2.26 shows the power output according to actual irradiance and temperature at the project location and another one is assumption (parameter mentioned above). According to the figures there are some oscillations, when there are frequent changes of irradiance and temperature. However, in stable conditions the model is very closely following the actual power that generated by the solar PV panels, which ensure effective P&O MPPT performance.

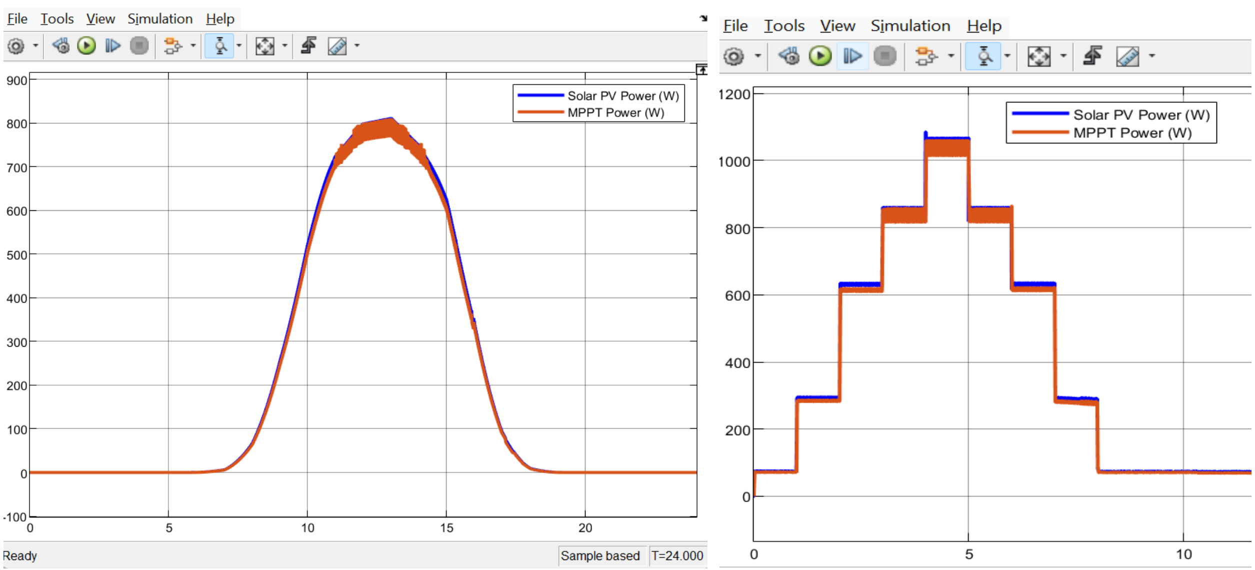

Figure 5.26: Power output curve of P&O MPPT algorithm

Under stable conditions the overall performance of P&O algorithm is near to 97.8%. The figure is given below.

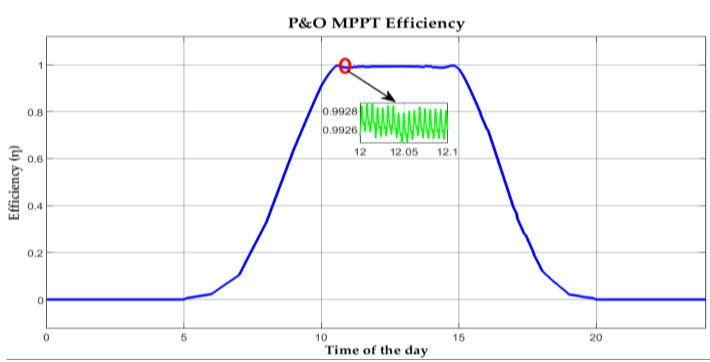

Figure 5.27: P&O MPPT algorithm efficiency curve

5.4.5 Predictive Control Method (PCM) MPPT Simulation Setup:

In this simulation setup, the predictive control method (PCM) MPPT technique was employed to enhance the tracking efficiency of solar generated power. To model included with DC-DC robust boost converter to regulate PV output voltage and optimal power extraction. Unlike traditional MPPT technique PCM has several advantages by leveraging system dynamics, fast convergence, and minimum MPP fluctuations. This MATLAB/Simulink model was designed to enhance response time, minimize power losses, and achieve a stable power output. This technique provides more stable output than the P&O technique for real time solar PV energy optimization. The MATLAB/Simulink model is given below with the boost converter.

MATLAB/Simulink Model (PCM Algorithm):

The MATLAB/Simulink model was developed for ideal and extreme environmental conditions. The model was incorporating with efficiency measurement blocks to evaluate the performance and power output.

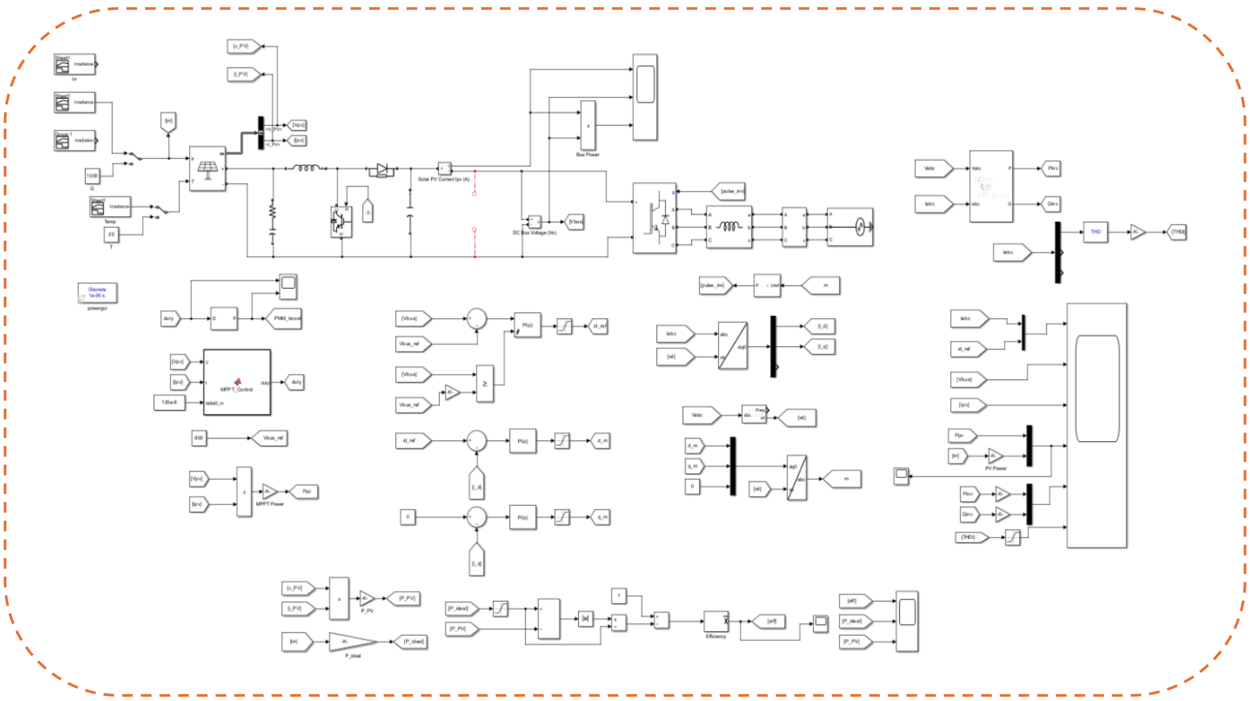

Figure 5.28: MATLAB/Simulink model for PCM MPPT algorithm

Results of PCM Technique (Output Curve):

The Predictive Control Method (PCM) MPPT automatically adjusts the duty cycle requirements by predicting the response of solar irradiance and temperature. PCM is not like conventional technique, it is not relied on continuous perturbation. It forecasts the optimal system operating point using the previous measurements.

Figure 5.29 illustrates the power output curve under ideal power generated by solar PV panels and PCM MPPT generated power at the project location and the second figure is assumption parameters (mentioned above). The results show that the PCM MPPT technique effectively tracks the MPP with lower oscillations, under extreme environmental conditions (irradiance, temperature). However, during the frequent changes of irradiance and temperature there are minor transient changes which occur as the model algorithm recalibrates duty cycle which maintain optimal PV power extraction. Despite this minor oscillation, PCM has accurate maximum power point tracking, strong adaptability. The PCM MPPT algorithm performance is 0.982 (98.2%), which ensures robust MPPT model for solar PV array.

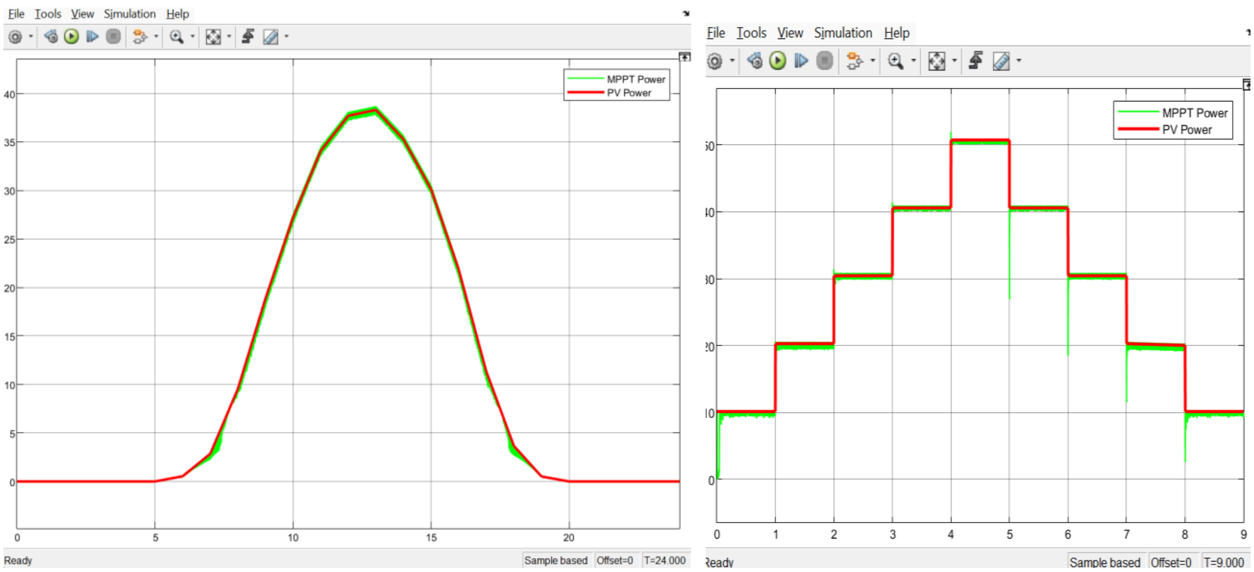

Figure 5.29: Power output curve of PCM MPPT algorithm

5.4.6 Fuzzy Logic MPPT Simulation Setup:

The Fuzzy Logic MPPT model implemented with a fuzzy logic controller block which tracks the solar PV panels maximum power point (MPP) by adjusting duty cycle of DC-to-DC boost converter. Fuzzy logic MPPT does not depend on traditional mathematical models instead it depends on expert define rules that can make real time decisions by input variables, such as changing voltage and power. The model setup consists of a solar PV array, DC-DC boost converter, a fuzzy logic controller, a pulse with modulation (PWM) generator, and peripheral model blocks. This fuzzy logic approach ensures accurate and rapid MPPT tracking, especially extreme environmental conditions.

MATLAB/Simulink Model (Fuzzy Logic Algorithm): This MATLAB/Simulink model was developed for both ideal and extreme environmental conditions. Fuzzy logic MPPT model implemented with efficiency measurement blocks that evaluate the model performance and power output.

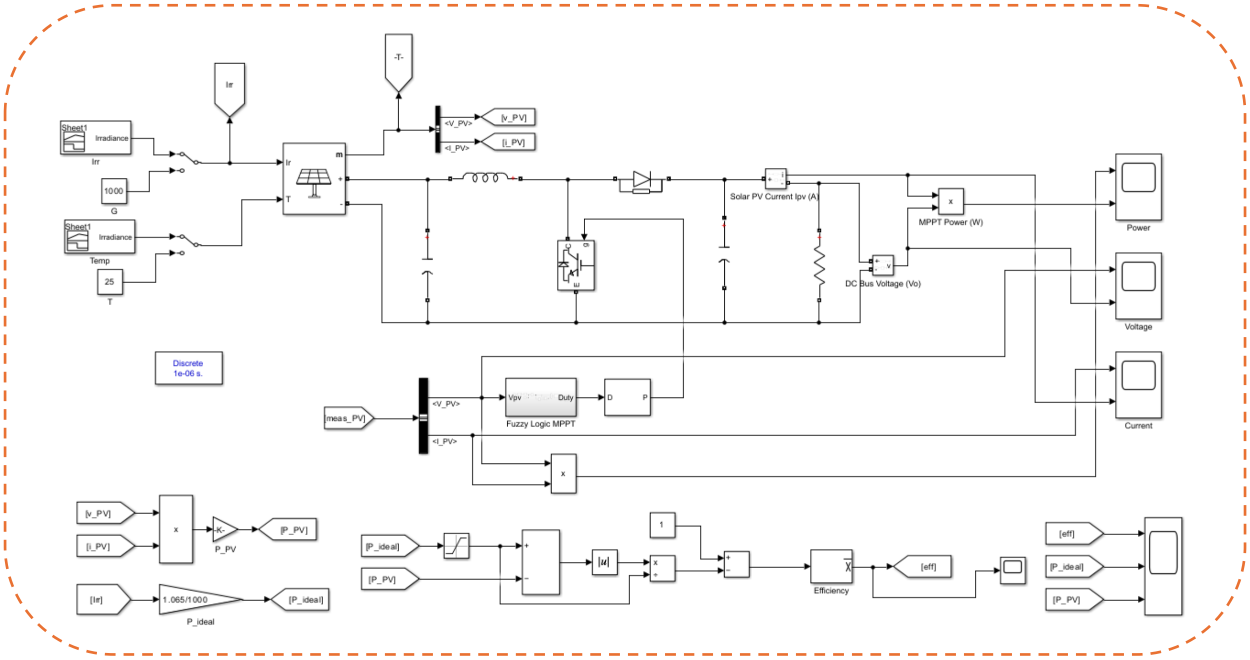

Figure 5.30: MATLAB/Simulink model for Fuzzy Logic MPPT algorithm

Results of Fuzzy Logic Technique (Output Curve):

The fuzzy logic MPPT technique intelligently optimizes the duty cycle by adapting environmental conditions. Fuzzy logic relies on rule-based decision system, which estimates and maintains the best efficient operating point for solar PV array. This fuzzy logic technique increases adaptability and ensures quick response according to dynamic changes of weather.

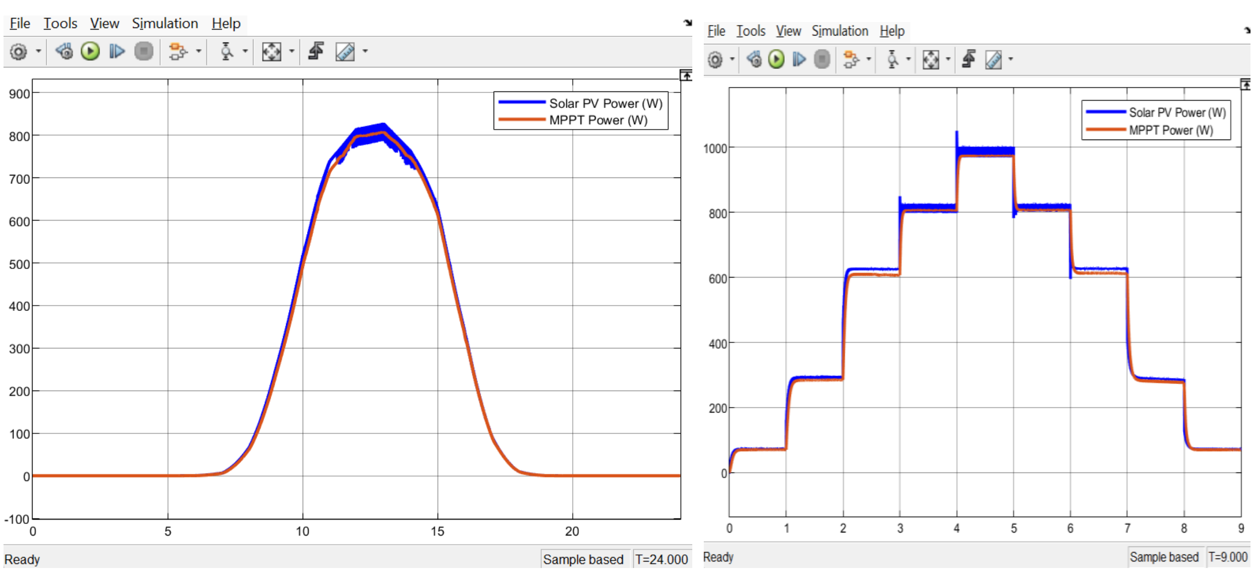

Figure 5.31: Power output curve of Fuzzy Logic MPPT algorithm

The output curve of the fuzzy logic MPPT model demonstrates stable and smooth tracking of solar PV arrays MPP with minimal tracking oscillations. Unlike traditional methods, it dynamically adjusts system duty cycle by linguistic rules. The figure 5.31 represents the comparison among theorical (ideal) power output form solar PV array and fuzzy logic MPPT algorithm power output (consider real data from the project location). The results of fuzzy logic MPPT technique indicates effective tracking of maximum power point and minimum oscillations. The figure shows even in actual solar PV generated power has oscillation in peak time, but fuzzy logic MPPT provides minimal oscillation for both conditions (ideal & real). Adaptation with the changes is very high for this MPPT technique. Although there are small transient variations during the fast shifting of solar irradiance and temperature, this controller adjusts very quickly and maintains optimal solar power output extraction. The fuzzy logic MPPT algorithm obtains high accuracy with the performance of 0.989 (98.9%), which makes it reliable and effective MPPT model for solar PV system.

5.4.7 Artificial Neural Network (ANN) MPPT Simulation Setup:

The Artificial Neural Network (ANN) based MPPT model was implemented for efficient tracking of solar PV array maximum power point (MPP). ANN technique has the capability to learn and adapt to changing environmental conditions. This ANN model is not like a conventional predefined technique; it is leveraging machine learning principles. It predicts optimal duty cycle form past and present input parameters, like solar voltage, current, irradiance, and temperature.

The ANN MPPT MATLAB/Simulink model was developed for both ideal and extreme weather conditions to evaluate model performance with the real dataset. The ANN model involves several layers of neurons, that are trained by historical data with complex recognize patterns. The model also includes efficiency measurement blocks for power extraction assessment of efficiency and accuracy. The model setup consists of a solar PV array, DC-DC boost converter, an ANN MPPT controller, a pulse with modulation (PWM) generator, and peripheral model blocks. This intelligent MPPT controller allows rapid response for solar irradiance and temperature, minimizes overall power losses and provides seamless stability of solar PV power generation.

MATLAB/Simulink Model (ANN Logic Algorithm):

The MATLAB/Simulink model is given below with all necessary Simulink books.

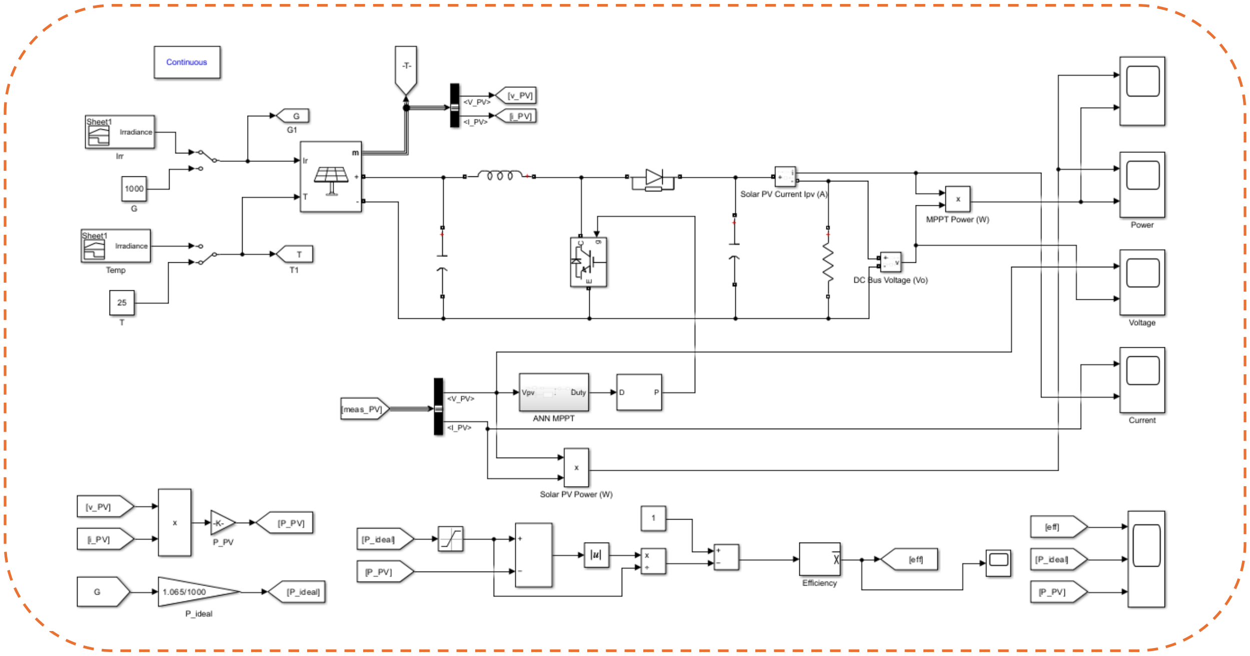

Figure 5.32: MATLAB/Simulink model for ANN MPPT algorithm

Results of ANN Technique (Output Curve):

The Artificial Neural Network (ANN) MPPT technique represents remarkable effectiveness of tracking the solar PV array maximum power point (MPP). In the real-world scenario, there are lots of fluctuations of solar irradiance and temperature, where ANN MPPT provides precise and reliable MPPT tracking with nominal oscillation. Unlike traditional method, the ANN MPPT technique proactively adapts irradiance and temperature variations and makes sure the solar PV arrays would be operated at optimal power point.

In this simulation, artificial neural network (ANN) MPPT algorithm was trained, tested, and validated using the real dataset that was forecasted before. The model was trained with the historical environmental dataset. To observe the model training accuracy (R^2), the Figure 5.33 is given below. The model shows training accuracy (R^2) value of 0.9994 (99.94%), and validation accuracy is 0.997 (99.7%) in the figure 5.33, that ensure strong fit among the actual data and model predicted data.

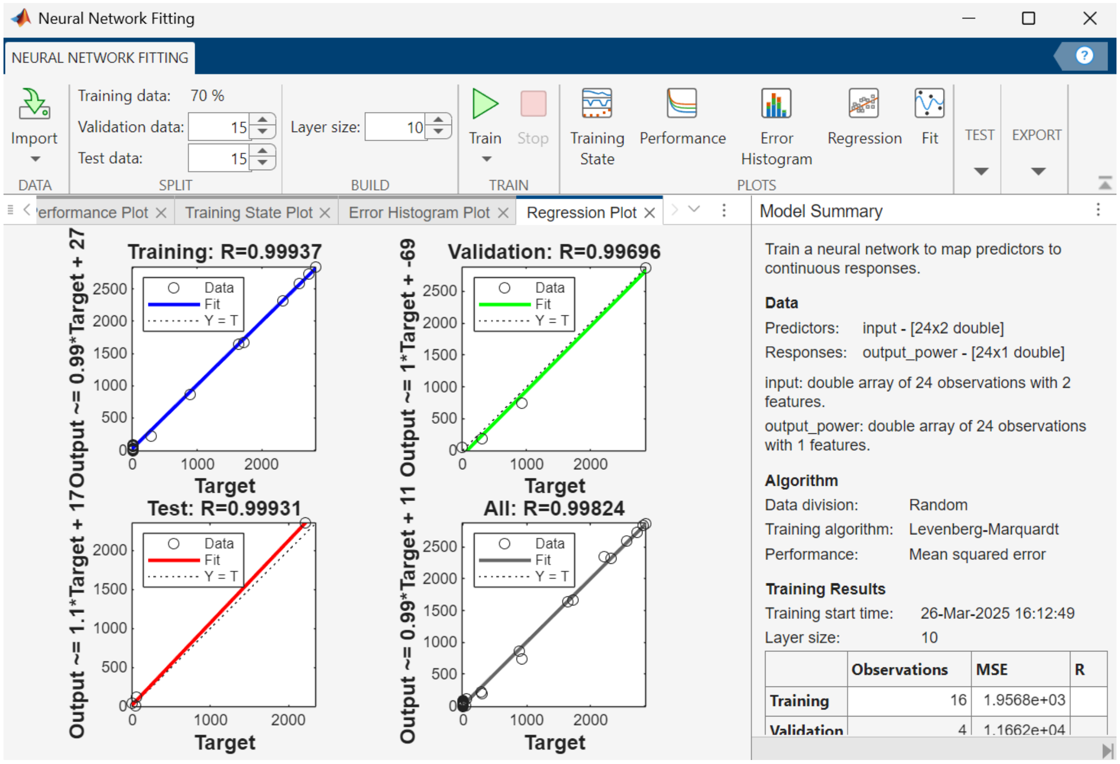

Figure 5.33: ANN MPPT algorithm training and validation

The simulation results show that the artificial neural network (ANN) MPPT algorithm precisely follows the maximum power point over a diverse spectrum of solar irradiance and temperature. It represents quick response to dynamic variations in environmental factors and maintains solar PV panels optimal operating point throughout the testing period. The output curve of the ANN model very closely aligns with actual generated power from solar PV panels, which effectively maximize the power output production.

In comparison among conventional MPPT algorithms, the ANN-based model shows superior performance, even in the case of rapid environmentally changing conditions. ANN MPPT ensures robustness for real world conditions, where solar PV generated power constantly changes. There are two different graphs in the figure 5.34, one is for ideal, and another is for real data (project site data). In ideal case, although there are some oscillations in actual solar generated power, the ANN MPPT generated solar PV power is very stable when no fluctuation occurs and its precisely follows the ideal power. Whereas, using the forecasted data (irradiance and temperature), solar PV generated power and ANN MPPT generated power is very closely aligned. Nevertheless, the artificial neural network (ANN) maximum power point tracking (MPPT) model provides the most reliable, fast and accurate MPPT algorithm compared to other MPPT algorithms. The simulation output curve is given below.

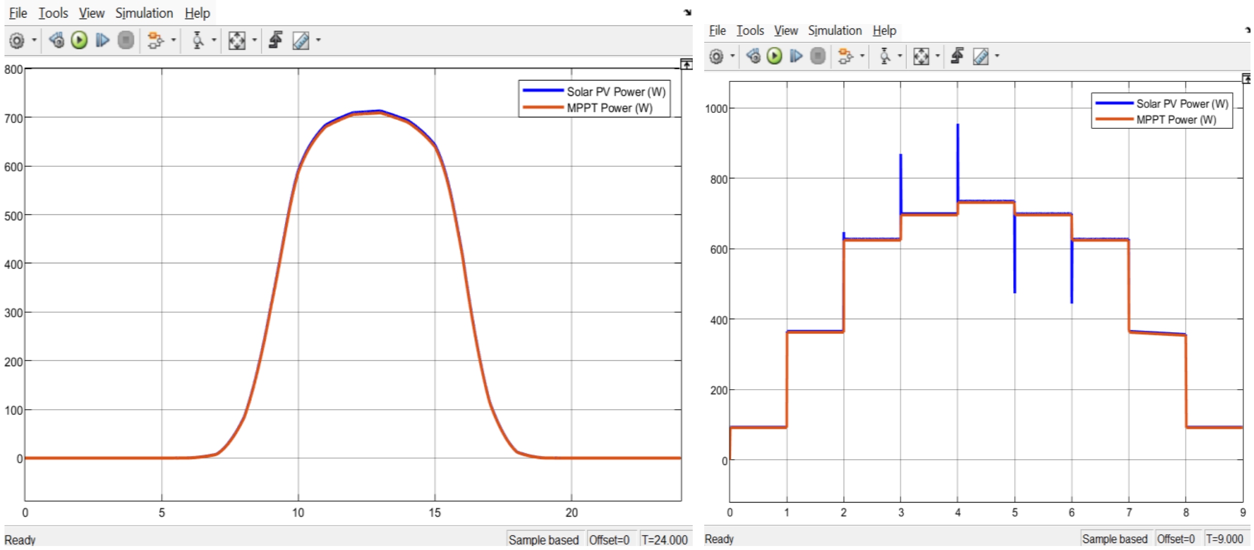

Figure 5.34: Power output curve of Fuzzy Logic MPPT algorithm

5.4.8 MPPT Model Performance Metrics Comparison

To evaluate the overall performance of each maximum power point tracking (MPPT) algorithms, the following metrics are considered. The performance metrics table is given below:

MPPT Algorithm	Tracking Efficiency (%)	Convergence Time (s)	Power Oscillations (W)	Computational Complexity
P&O	97.8%	0.45	±5 W	Low
PCM	98.2%	0.18	±2 W	Medium
Fuzzy Logic	98.9%	0.12	±1 W	High
ANN	99.7%	0.10	±0.5 W	Very High

Table 5.8: MPPT algorithm performance metrics

There are four most important metrics there. The steady state tracking efficiency indicates which one is the best among the four different MPPT algorithms. Where artificial neural network (ANN) MPPT model achieves the highest tracking efficiency (99.6%). One of the crucial factors of MPPT model is convergence time. It indicates how fast MPPT algorithm reaches to the solar PV panels maximum power point (MPP) with the STC and extreme environmental conditions. As shown in table 5.9, ANN MPPT algorithm achieves the fastest convergence time of 0.10 seconds, whether P&O MPPT algorithm is the lowest convergence time of 0.45 seconds. Also, there were power losses due to oscillation. ANN MPPT demonstrates the lowest power losses and P&O MPPT algorithm gains the highest power losses.

5.4.9 Discussion

The results of four different maximum power point tracking (MPPT) algorithms indicate each of the models have some benefits and drawbacks. While conventional MPPT algorithms such as P&O are less complex and easy to implement in hardware and cost efficient. But there are some limitations like low efficiency, slow convergence, high power losses, and high oscillation. Predictive control method (PCM) and Fuzzy logic MPPT controller provide better performance compared to P&O MPPT, but they have higher requirement for hardware (computational) to process the signals. Artificial neural network (ANN) MPPT algorithm offers the highest performance and quick response time, but it also requires high computational hardware that increases the cost. Moreover, among the four different MPPT algorithms, ANN MPPT model is the best one to choice to extract the maximum power from the solar PV panels [102-104].

Summary of Main Findings

Performance Criteria	Best MPPT Algorithm
Convergence Speed	ANN
Efficiency	ANN & Fuzzy Logic
Response to Changes	ANN
Computational Complexity	P&O

Table 5.9: Performance evaluation of MPPT algorithms

The most suitable model depends on the application requirements. The recommended models are:

- **Standalone Solar PV Systems**: P&O or PCM MPPT models are suitable, due to less complexity and cost.
- **Grid Connected Solar PV Systems**: ANN or Fuzzy logic MPPT models are suitable for high accuracy and stable power.

5.5 Smart Hybrid Microgrid System Modeling in MATLAB Simulink

5.5.1 Model Description

Overview of the MATLAB Simulink Model

The MATLAB/Simulink model was developed for this research indicate a Smart Hybrid Microgrid System (SHMs) incorporating solar and wind energy resources with Battery energy storage system (BESS). The architecture of this consists of three main components, such as solar photovoltaic (PV) arrays, wind turbine, and BESS. The model is structured according to load energy demand per day (24 hours). It represents the dynamic response among those components and the grid, that ensures SHMs can manage energy generation, storage and distribution effectively. The typical parameters are considered (irradiance, ambient temperature, wind speed, load demand) to simulate the model. The model is also properly connected with a control system, so that it can manage generation, storage and distribution.

SHMs Components:

1. **Solar PV Panels:** The standard PV panels block is used in the MATLAB/Simulink environment, that accurately captures electrical behavior under diverse environmental conditions. The parameters are given in table 5.10, that perfectly represents the ratio of electrical output and incident of solar radiation. The temperature coefficient effect is also considered, because it has effect on peak power, open circuit voltage and current.
2. **Wind Turbine:** The mathematical model was developed to simulate wind power to electrical power. The model parameters are included with rated power, that is the maximum power (kW) of a wind turbine can generate under optimal wind conditions. The model is incorporated with power curves to make the relationship among wind speed and power generation, that allows accurate simulation and observe the performance under diverse wind conditions.
3. **Battery Energy Storage:** The battery energy storage system model was developed in MATLAB/Simulink to store the energy and deliver when additional power is needed to balance supply and demand within SHMs. BESS is also essential for grid integration to maintain grid stability. The BESS is model was included with control system so that it can maintain state of charge (SoC) limits, and depth of discharge (DoD) limits to prevent over charging and discharging.

MATLAB Simulink model is a powerful tool to simulate SHMs incorporating all those components. It allows the analysis of the model performance and dynamic assessments which enable researchers and practitioners to optimize SHMs design and analysis for various applications.

5.5.2 Simulation Setup Sizing Optimization:

To design optimized Smart hybrid microgrid system (SHMs) that cover 24 hours energy demand of the proposed location (Ericeira, Lisbon), the proper optimal component sizing is required. To determine the capacity of solar PV panels, wind turbines, and energy storage system, calculations are given below.

Daily Energy Demand: According to the previous assessment, the proposed location daily energy demand is: 125.82 kWh, where hourly average demand is: 5.24 kWh, hourly peak demand is: 6.71 kWh and average monthly peak demand is: 155.72 kWh. The details are provided in Table 5.1.

1. Solar PV Panels Capacity Calculation: The solar PV panel's total capacity is calculated by the panel specification datasheet (Table 5.7). Also, the hourly average solar irradiance, and temperature data are considered to calculate actual power output.

PV Power Output Calculation:

i. The mathematical expression of solar cell temperature is:

$$T_{cell} = T_{amb} + \frac{G\ .\ (NOCT-20)}{800} \tag{5.2}$$

ii. Temperature-Corrected for DC Power

$$P_{corrected} = P_{panel} \times (1 + (\alpha_p \times (T_{cell} - T_{STC})) \tag{5.3}$$

Where,

$P_{corrected} = Power\ output\ with\ actual\ cell\ temperature\ [W]$
$P_{panel} = PV\ rated\ power\ at\ STC\ [W]$
$\alpha_p = Power\ coefficient\ temperature$ [°C]
$T_{cell} = PV\ Cell\ temperature$ [°C]
$T_{STC} = Temperature\ at\ STC$ [°C]

iii. Solar PV Energy Calculation

$$E_{hour} = \left(\frac{P_{panel}}{1000}\right) \times \eta_{panel} \times A_{panel} \times G \tag{5.4}$$

Where,

$E_{hour} = Energy\ production\ by\ hours\ [Wh]$
$\eta_{panel} = PV\ efficiency\ [W]$
$\alpha_p = Power\ coefficient\ temperature$ [°C]
$A_{panel} = PV\ area$ [m²]
G = Solar Irradiance [W/m²]

iv. Total Daily Energy production:

$$E_{total} = \sum_{h=0}^{23} E_{hour}(h) \tag{5.5}$$

$$E_{total\ (kWh)} = \frac{E_{total}}{1000} \tag{5.6}$$

To calculate accurate solar PV power, it is essential to consider all the meteorological (real) data, that can affect power production. This approach ensures actual power production from the proposed location. The table is given below to observe per day energy production.

Hour	Irradiance (W/m²)	Ambient Temp (°C)	Power Generation (W)
0	0.00	14.56	0.00
1	0.00	14.40	0.00
2	0.00	14.26	0.00
3	0.00	14.13	0.00
4	0.00	14.02	0.00
5	0.00	13.92	0.00
6	10.61	13.85	2.35
7	56.27	14.04	12.48
8	188.20	14.54	41.67
9	371.93	15.33	82.11
10	536.58	16.18	118.10
11	671.83	16.91	147.49
12	743.28	17.45	162.86
13	755.23	17.78	165.28
14	695.30	17.91	152.09
15	594.19	17.85	130.00
16	431.04	17.60	94.39
17	223.49	17.17	49.02
18	72.19	16.59	15.87
19	10.18	15.98	2.24
20	0.00	15.46	0.00
21	0.00	15.14	0.00
22	0.00	14.91	0.00
23	0.00	14.72	0.00

Table 5.10: Per day solar power generation from one PV panel (213.15 Wp)

Total daily PV generated energy = 1175.95 Wh = 1.175 kWh.

So, using 213.15 Wp PV, it will generate 1.175 kWh of energy per day.

- Total number of PV panels needed = $\frac{Deaily\ Energy\ Demand}{Energy\ Generation\ per\ Panel}$

$$= \frac{125.82\ kWh}{1.175\ kWh} = 107.08 = 108\ pcs\ of\ PV$$

- Total PV Capacity = 108 x 0.21315 kW = 23.02 kWp

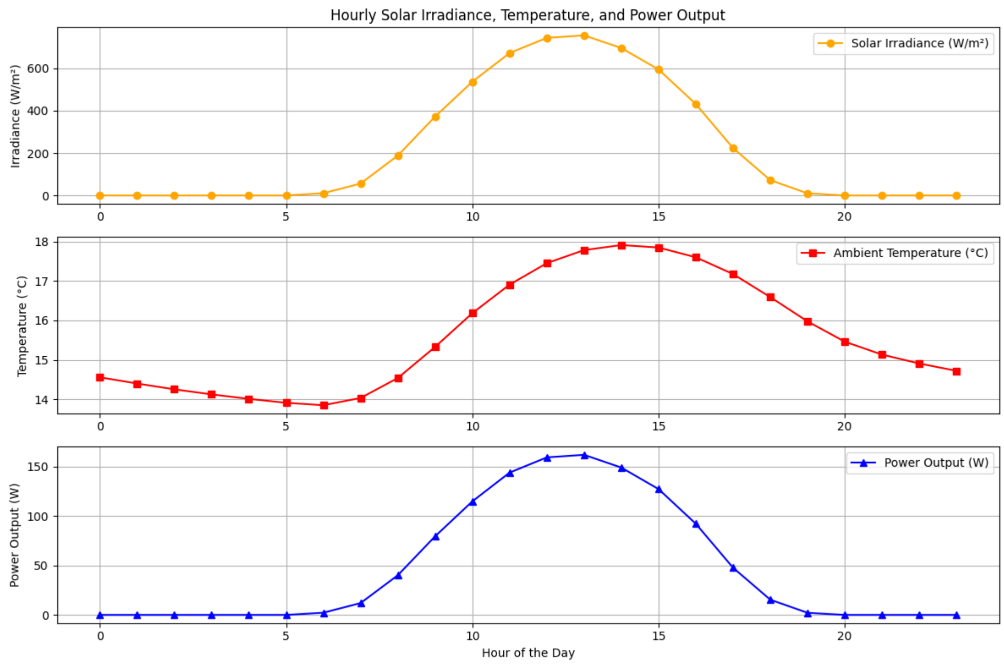

Figure 5.35: Hourly solar PV power generation

2. Wind Turbine Capacity Calculation: The calculation of the precise power from wind turbine depends on the hourly wind speed data. According to the hourly wind speed data the wind power generation function is divided into four different ranges, so that it can cover whole range of wind speed (0 m/s to 25 m/s). To calculate the wind turbine power Table 5.11 dataset are used.

Wind Turbine Power Calculation:

a) The mathematical expression of wind turbine power output is:

$$P(v) = \begin{cases} 0 & if\ v < 3\ m/s \\ P_{rated} \cdot \left(\frac{v - v_{in}}{v_{rated} - v_{in}}\right)^3 & if\ 3 \leq v \leq 12\ m/s \\ P_{rated} & if\ 12 \leq v \leq 25\ m/s \\ 0 & if\ v > 25\ m/s \end{cases} \tag{5.7}$$

Where,

$P_{rated} = Wind\ turbine\ rated\ power\ (7.5\ kW)$
$v_{in} = Cut\ in\ wind\ speed\ (3\ m/s)$
$v_{rated} = Rated\ wind\ speed\ (12\ m/s)]$

b) Wind turbine hourly energy generation:

$$E_{hour} = P_{hour} \times 1\ hour \tag{5.8}$$

Where,

$$P_{hour} = Each\ hour\ power\ output$$

C) Total wind generation by 24 hours:

$$E_{total} = \sum_{h=0}^{23} E_{hour}(i) \tag{5.9}$$

Where,

$$E_{hour}(i) = Energy\ generated\ by\ hours\ i - th$$

Wind Turbine Specifications:

- Rated Power (P_{rated}): 7.5 kW
- Cut-in Speed (v_{in}): 3 m/s
- Rated Speed (v_{rated}): 12 m/s
- Cut-out Speed (v_{out}): 25 m/s

Using 24-hours of wind speed data and precise wind power calculation formula, the following power table 5.11 is prepared. It provides an hourly overview of the wind power generation.

Hour	Wind Speed (m/s)	Power (W)	Energy (Wh)
0	6.17	327.73	0.33
1	6.10	306.49	0.31
2	6.05	291.90	0.29
3	6.04	289.04	0.29
4	6.02	283.37	0.28
5	6.01	280.56	0.28
6	5.99	275.01	0.28
7	5.94	261.44	0.26
8	6.02	283.37	0.28
9	6.08	300.60	0.30
10	6.17	327.73	0.33
11	6.25	353.17	0.35
12	6.37	393.75	0.39
13	6.56	464.18	0.46
14	6.79	560.08	0.56
15	6.97	643.73	0.64
16	7.08	698.74	0.70
17	7.04	678.39	0.68
18	6.90	610.28	0.61
19	6.74	538.21	0.54
20	6.60	480.00	0.48
21	6.49	437.33	0.44

22	6.38	397.27	0.40
23	6.28	363.04	0.36

Table 5.11: Per day wind power generation from one turbine (7.5 KW)

Total daily generated wind energy = 9845.40 Wh = 9.85 kWh.

So, using 7.5 kW wind turbine, it will generate 9.85 kWh of energy per day.

- Total number of wind turbine needed = $\frac{Deaily\ Energy\ Demand}{Energy\ Generation\ per\ wind\ turbine}$

$$= \frac{125.82\ kWh}{9.85\ kWh} = 12.77 = 13\ pcs\ wind\ turbine$$

- Total Wind Turbine Capacity = 13 x 7.5 kW = 97.5 kW

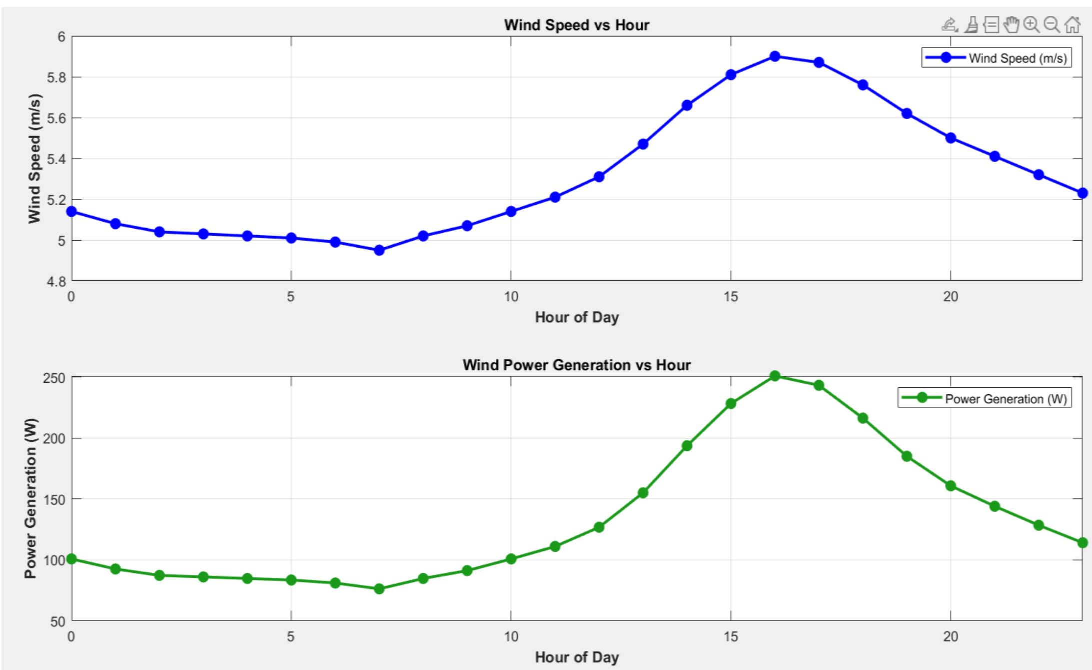

Figure 5.36: Hourly wind turbine power generation

3. Hybrid System Optimization

To design a smart hybrid microgrid system for the proposed location, energy balance is required. Daily energy demand of the proposed location is 125.82 kWh. For this research we consider 60% will be solar PV power and 40% of the wind power for reliability.

- Solar contribution = $125.82\ kWh \times 60\% = 75.49\ kWh$
- Required panels $= \frac{75.492\ kWh}{1.175\ kWh} = 64.25 = 65\ PV\ panels$
- **Solar Capacity** $\boldsymbol{= 65 \times 213.15\ Wp = 13.85\ kW}$

- Wind contribution = $125.82\ kWh\ \times 40\% = 50.33\ kWh$
- Required turbines $= \frac{50.33\ kWh}{9.85\ kWh} = 5.11 = 6\ Wind\ turbines$
- **Wind Capacity** $= \mathbf{6\ \times 7.5\ kW\ = 45.0\ kW}$

a. Solar and Wind Contribution:

The combination is considered **60% solar + 40% wind** for SHMs energy mixed.

Component	Capacity	Daily Energy	Adjusted Energy
Solar	23.02 kW	125.82 kWh	75.5 kWh
Wind	45.00 kW	59.10 kWh	52.00 kWh
Total			**127.50 kWh**

Table 5.12: Energy mixed within the SHMs

4. Battery Storage Sizing

Step 1: According to daily solar energy production data from 8 PM to 6 AM, there is no available sunlight. Hence PV will not generate any energy that time.

Total energy required at nighttime (8 PM – 6 AM):

10 hours × 5.24 kWh = 52.4 kWh.

Where, 5.24 kWh average hourly demand.

Total energy production by wind turbines (according to hourly data).

$$\sum Wind(8\ PM - 6\ AM) = 19.79\ kWh$$

Deficit: 52.4 kWh – 19.79 kWh = **32.61 kWh**

Step 2: Battery capacity calculation.

To get the optimal power output from battery, it should be maintaining industry standard for charging and discharging.

- Battery depth of discharge (DoD): 80%
- Battery round trip efficiency: 90%

Battery Capacity: $\frac{32.61\ kWh}{0.8\ \times 0.9} = 45.30\ kWh$

Step 3: Safety Margin

To enhance the battery energy storage safety, longevity, and reliability of 20% buffer should be calculated, so that it can maintain seasonal variability.

$$\textbf{Battery Capacity}_{\textbf{safety}}: 45.30\ kWh\ \times 1.2 =\ 54.36\ kWh$$

Step 4: Autonomy Calculation

$$\textbf{Battery Capacity}_{\textbf{autonomy}}: 2\ \times 54.36\ kWh = 108.72\ kWh$$

Smart Hybrid Microgrid System (SHMs) design requirements.

Component	Capacity	Remarks
Solar	23.02 kWh	108 PV Panels (213.15 W each)
Wind	45.00 kWh	6 Wind turbines (7.5 kW each)
Battery	54.36 kWh	90% efficiency, 80% DoD

Table 5.13: Components sizing of SHMs

- **Energy Balance = Demand – (Solar PV + Wind + Battery)**

Energy Management Validation:

- **Daily demand:** 75.50 kWh (Solar) + 52.00 kWh (Wind) = **127.50 kWh** (match the demand)
- **Peak demand:** 10.7 kWh (Solar) + 3.14 kWh (Wind) = **13.84 kWh** > **7.16 kWh** (sufficient)
- **Battery Usage:** Battery charges fully using surplus energy, discharges **54.36 kWh** at night.

To observe better ways, the table is presented:

Hours	Solar (W)	Wind (W)	Energy Demand (W)	Battery (W)
0	0.00	1918.80	4350.21	-2431.41
1	0.00	1833.20	3878.48	-2045.28
2	0.00	1787.12	3583.67	-1796.55
3	0.00	1762.96	3400.53	-1637.57
4	0.00	1748.28	3361.22	-1612.94
5	0.00	1735.00	3543.92	-1808.92
6	152.75	1711.24	4029.09	-2165.10
7	811.20	1665.52	4679.04	-2202.32
8	2708.55	1756.28	5240.54	-775.71
9	5337.15	1822.28	5615.67	1543.76
10	7676.50	1916.00	5817.82	3774.68
11	9586.85	2022.32	5959.67	5649.50
12	10585.90	2167.40	5928.30	6825.00
13	10743.20	2416.68	5744.26	7415.62
14	9885.85	2714.96	5623.50	6977.31

15	8450.00	2989.92	5560.78	5879.14
16	6135.35	3142.32	5657.99	3619.68
17	3186.30	3096.52	6020.58	262.24
18	1031.55	2892.48	6679.50	-2755.47
19	145.60	2659.40	7161.38	-4356.38
20	0.00	2461.32	6963.19	-4501.87
21	0.00	2321.04	6382.00	-4060.96
22	0.00	2177.84	5666.94	-3489.10
23	0.00	2039.60	4966.40	-2926.80

Table 5.14: Hourly solar, wind and battery storage calculation

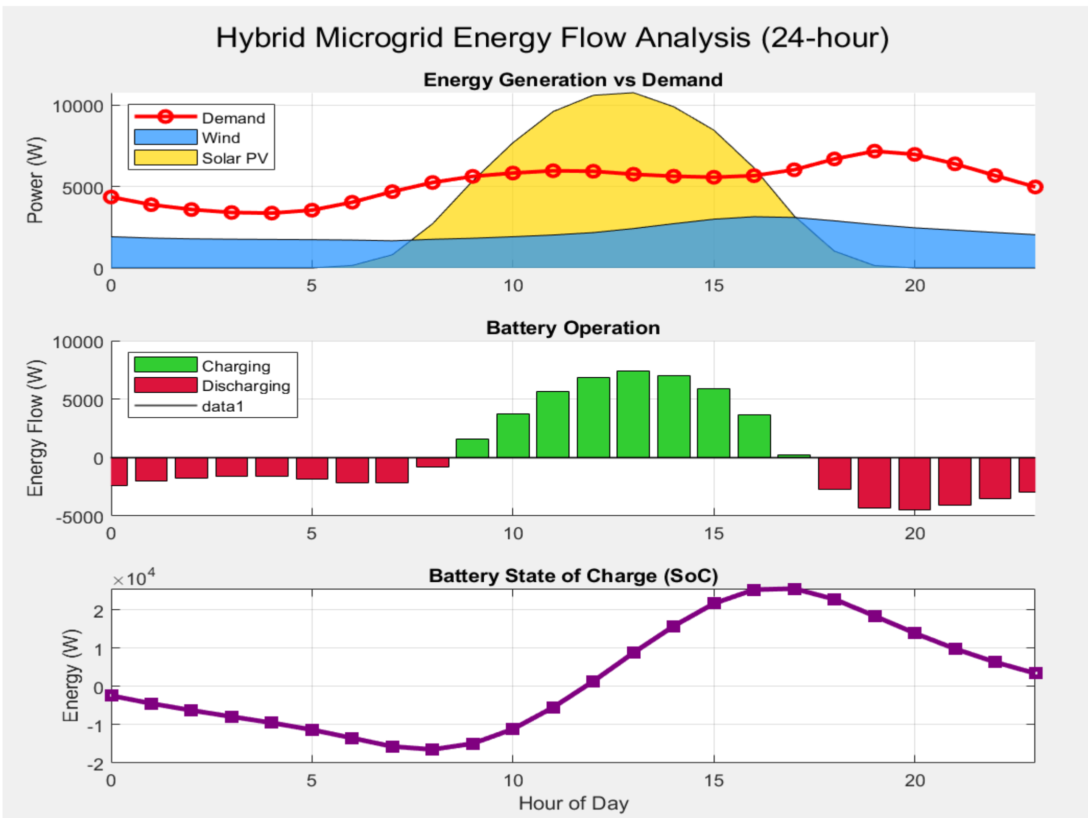

Figure 5.37: SHMs overall energy management system

The first graph represents solar dominating in daytime and charging the battery system with the surplus energy. Wind partially fulfills the demand, and the battery covers the remaining energy.

5.5.3 SHMs MATLAB/Simulink Simulation Setup:

The MATLAB Simulink model developed for this study represents a hybrid microgrid system integrating multiple renewable energy sources with energy storage and load management strategies. The model simulates real-world operational scenarios to assess system efficiency, reliability, and sustainability.

System Architecture in Simulink: The Simulink model architecture is integrated with PV arrays, MPPT DC-DC boost converter, wind turbine, battery energy storage, power electronics inverter, peripheral circuit breakers, and measurements blocks.

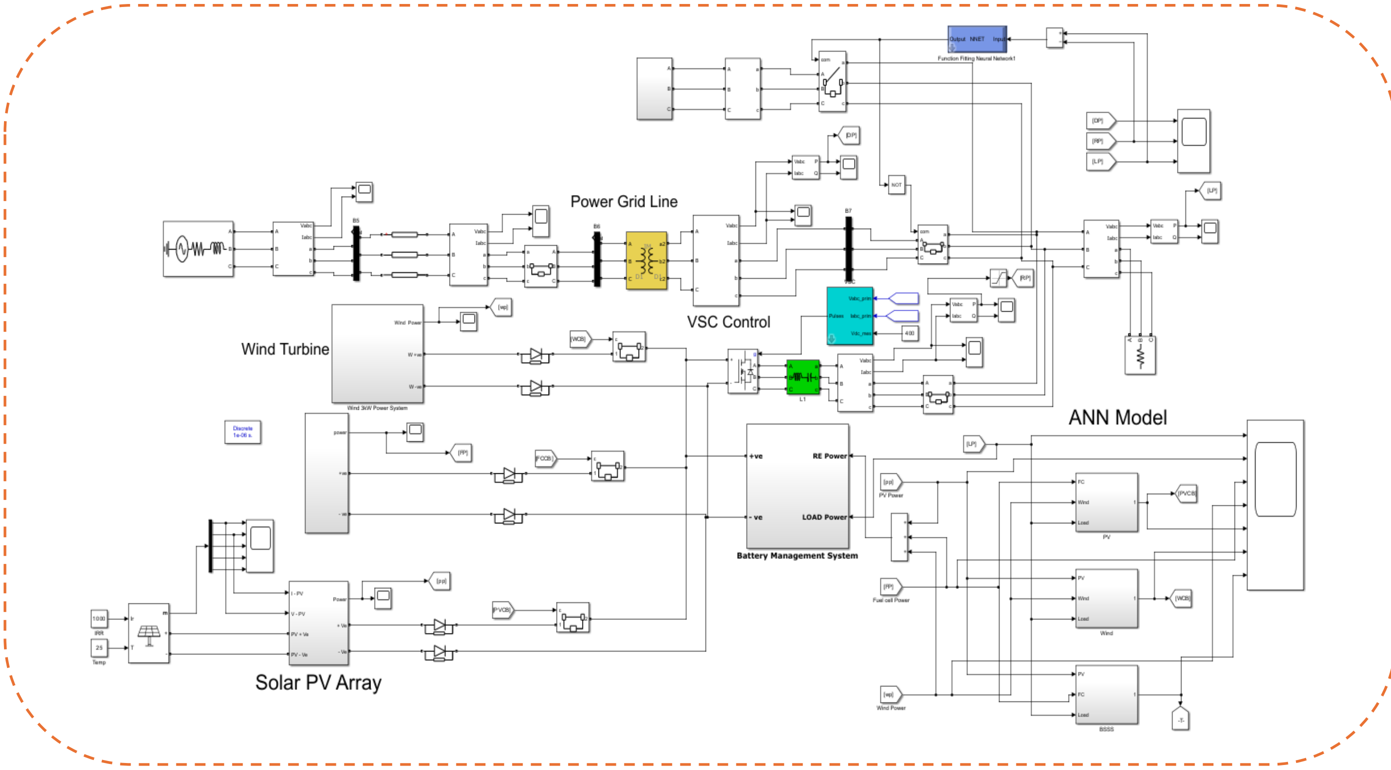

Figure 5.38: MATBAL/Simulink model of SHMs

Wind Turbine Model:

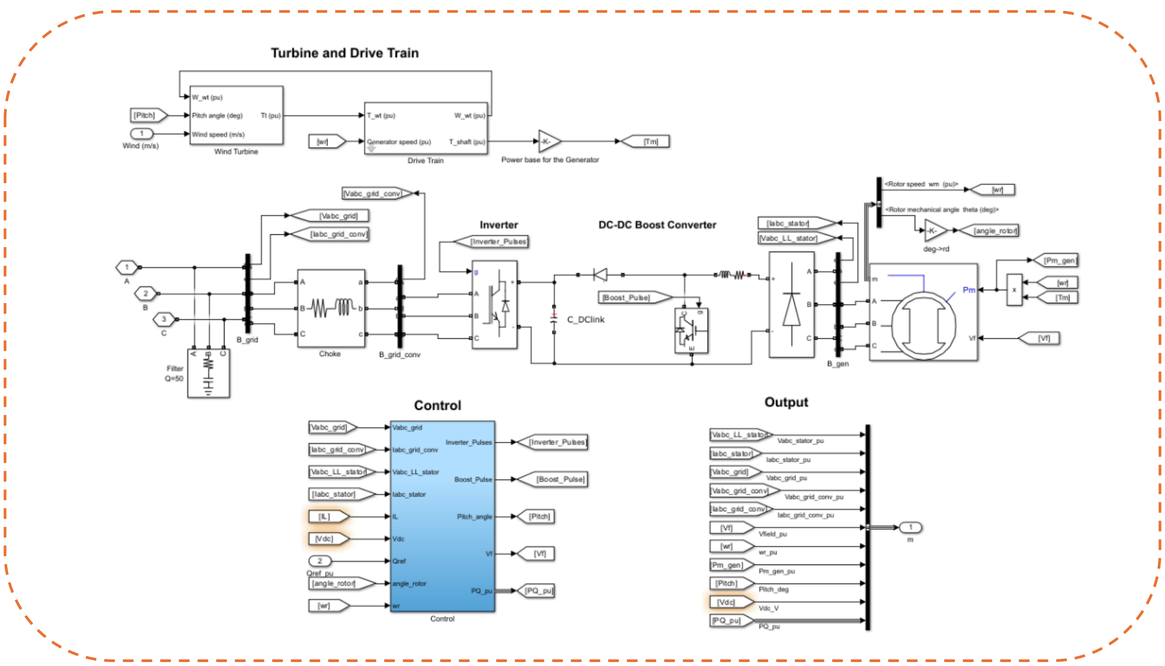

Figure 5.39: Wind turbine MATLAB/Simulink modeling

Battery Control Model:

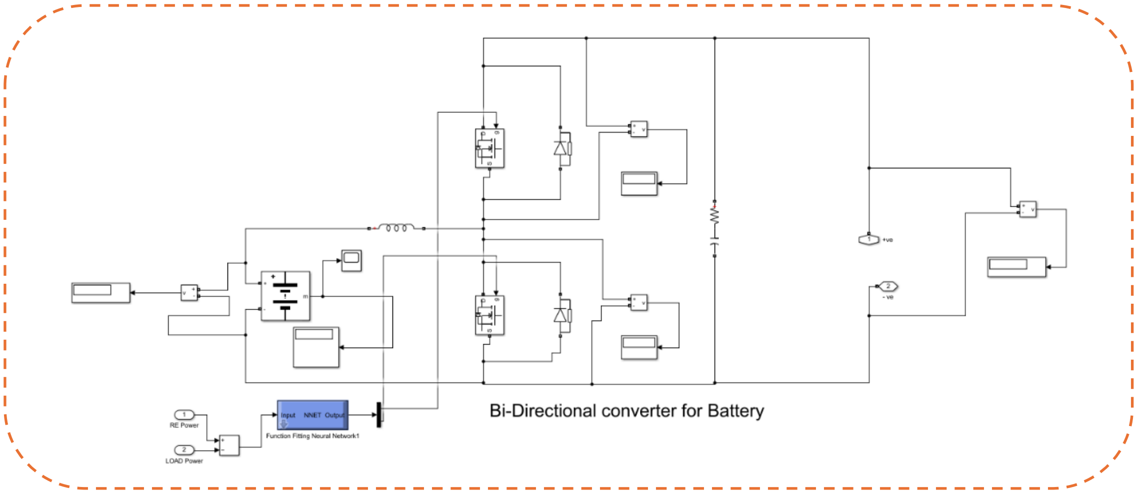

Figure 5.40: Battery control MATLAB/Simulink modeling

5.5.4 SHMs MATLAB/Simulink Simulation Results and Discussion:

The MATLAB/Simulink model was developed using all the available meteorological data. The forecasted dataset (demand, irradiance, temperature, wind speed) was used to simulate the model. The smart hybrid microgrid system simulation results is given below:

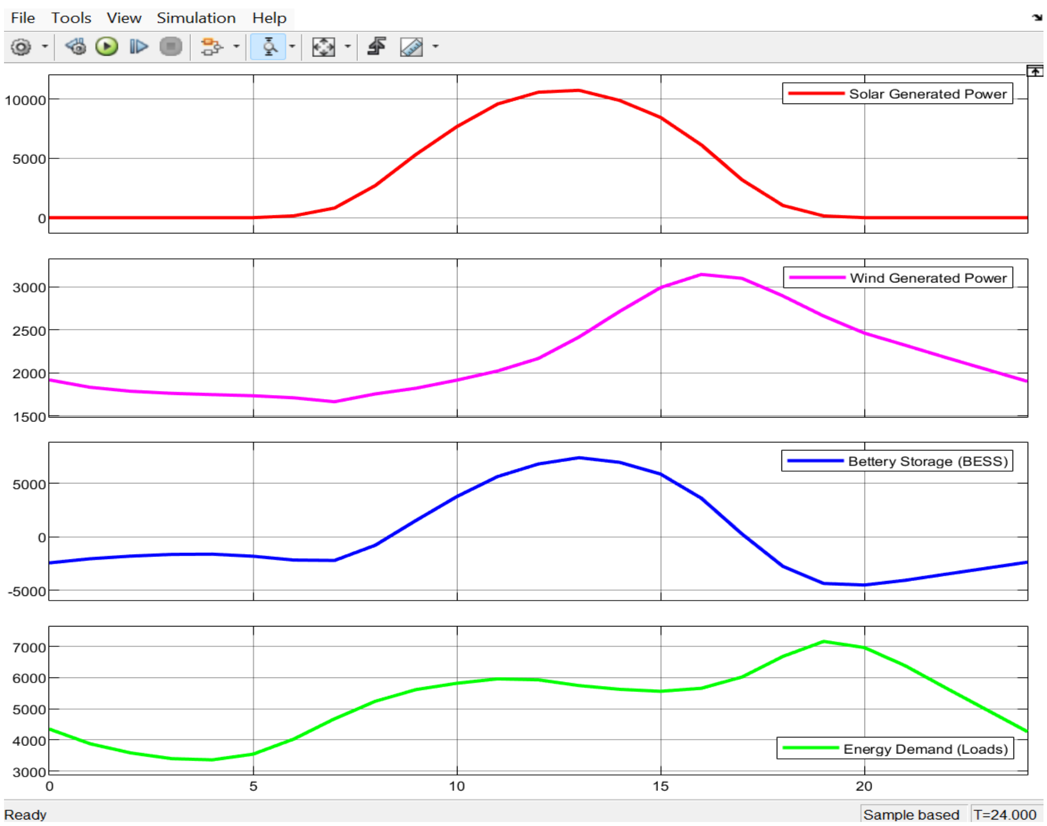

Figure 5.41: SHMs simulation for energy balance

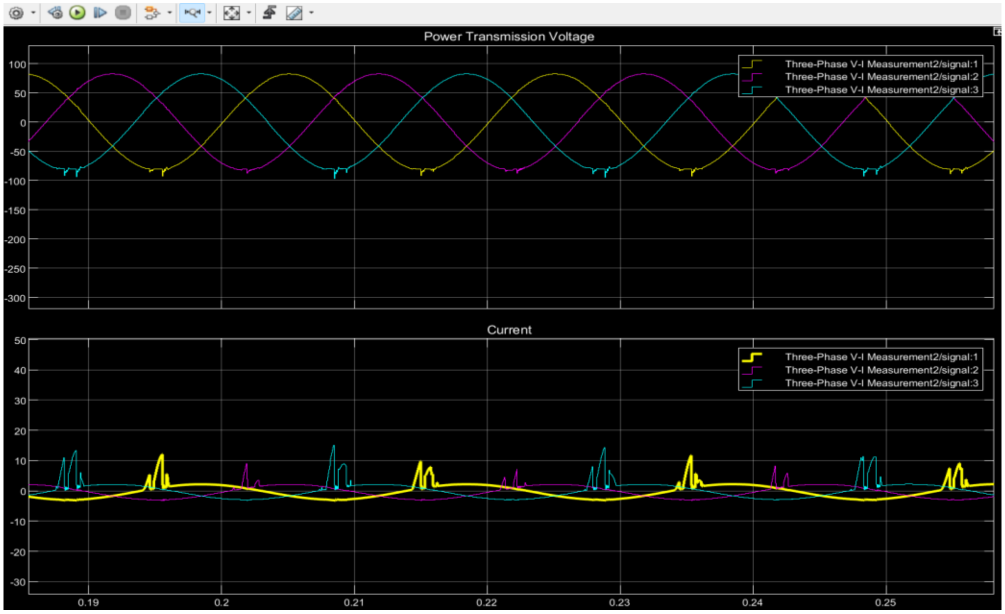

Figure 5.42: SHMs voltage and current fluctuation during rapid changes

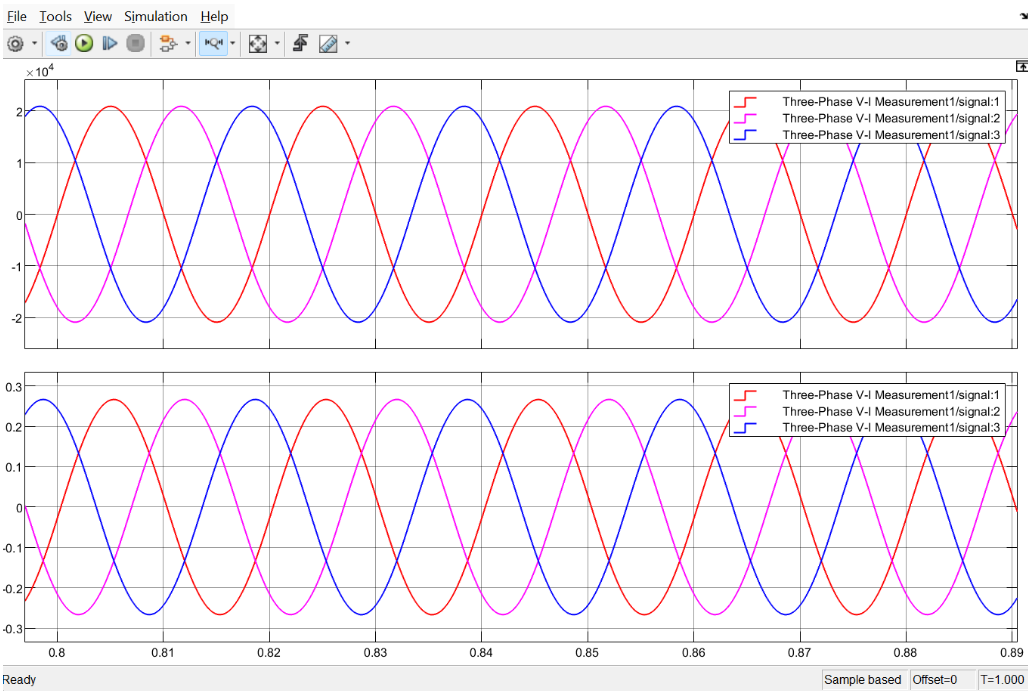

Figure 5.43: AC power distribution in the grid network

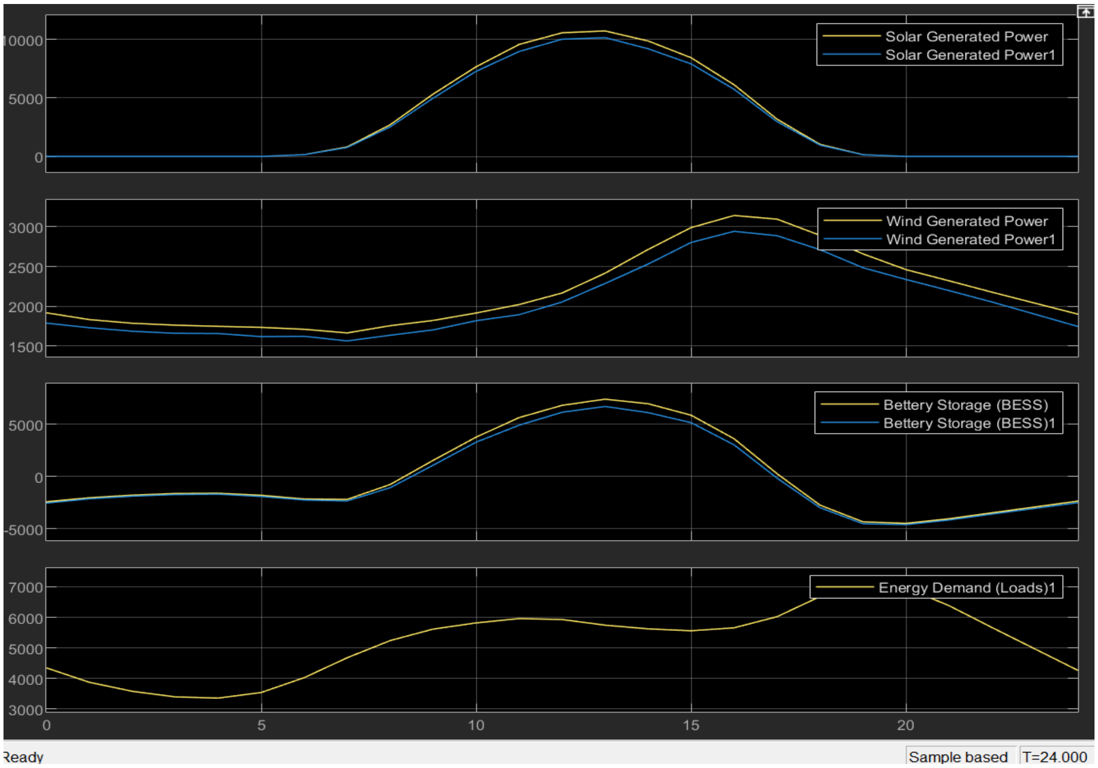

Figure 5.44: Theorical and SHMs model generation comparisons

Discussion

The Smart Hybrid Microgrid System (SHMs) is demonstrating the promising results through the grid network. The SHMs are simulated to comprehensive analysis of the output results (Power output, Efficiency, Grid stability, Load management), in MATALB/Simulink environments. The model is integrated with solar PV panels, wind turbines, battery energy storage systems, DC-DC boost converter, bidirectional converter (battery control), and environmental factors. This method allows SHMs detailed investigation and analysis of dynamic behavior.

The performance of the SHMs is evaluated compared to theorical renewable energy generation and the MATLAB/Simulink model generated energy. According to the results of Simulink model performance 97.4%, which ensures accuracy and reliability of SHMs. The Simulink model successfully covers the energy demand per hour. Although there are some fluctuations in the voltage and current, because of high renewable energy resource fluctuations. But the control system recovers quickly. Due to fluctuations, some electrical losses have occurred.

The limitation of this model is that it requires robust modeling for control and energy management systems. Energy management is one of the most important parts for designing smart hybrid microgrid systems (SHMs). In this model is not integrated with real time monitoring systems. Hence if there are any technical and environmental issues, it cannot be provided optimal power output, although this system is modeled using long term solar irradiance, temperature and wind speed data. For further research large scale system can be explored, with real time monitoring and control algorithms.

Chapter 6

Conclusion

This study on Smart Hybrid Microgrid Systems (SHMs) incorporating Renewable Energy Resources (REs) and Battery Energy Storage System (BESS) provides valuable information into renewable energy resource assessments, technical design, energy demand forecasting, and optimization which is crucial for sustainable and reliable grid integration. The research begins with a comprehensive review of existing SHMs, their energy demand and REs forecasting techniques, SHMs modeling, optimization methods with associated challenges and advantages.

The main aspect of this study was the analysis of SHMs with renewable energy resources and energy storage system for grid integration. To integrate multiple renewable energy sources, a battery storage system with the grid is crucial, due to rapid RE generation fluctuation. It impacts on grid stability and reliability. Hence Long Short-Term Memory (LSTM) machine learning model was developed to predict energy demand and generation of the project location. The LSTM model demonstrates high accuracy for solar irradiance, temperature, and wind speed with MAE: 0.23 (W/m^2), 0.18 (°C), 0.78 (m/s), RMSE: 0.49 (W/m^2), 0.26 (°C), 1.14 (m/s), and R^2: 94%, 99%, 97% respectively. This level of accuracy is critical for effective grid integration with SHMs, that can response very fast with the generation and demand changes.

To extract the maximum power from solar PV arrays MATLAB/Simulink model was used, that allow detail simulations and performance analysis. Maximum Power Point Tracking (MPPT) algorithms, like Perturbation and Observation (P&O), Predictive Control Method (PCM), Fuzzy Logic, and Artificial Neural Network (ANN) are used for comparative analysis and find the best fitted MPPT algorithm for optimizing the output power. The MPPT algorithms demonstrates the Tracking efficiency, Convergence time, Power oscillations and Computational complexity. Among those four (4) MPPT, the ANN-based MPPT showed the highest tracking efficiency of 99.7%, convergence time 0.1 second, power losses ±0.5 W due to oscillations. ANN MPPT has a drawback of very high computational complexity that increases the cost.

This research also highlighted the importance of DC-DC boost converter design to control the DC bus voltage. The peripheral components ensure seamless operation and reliability of SHMs, that contribute grid stability and resilience. The result of this study demonstrates the potential Smart Hybrid Microgrid System (SHMs) has to provide reliable and sustainable energy solutions for multiple applications, including islanded areas, community-based systems, and commercial establishments. The key findings of this study include high accuracy of forecasting model, power generation optimization, incorporate REs and BESS for grid stability and reliability, technical feasibility.

Future Work and Recommendations

The findings of this study open several opportunities for future work. For demand and generation forecasting models can be improved by using hybrid models, like Auto Regression AR, LSTM, and Conventional Neural Network (CNN) together. Also power optimization MPPT techniques can be hybrid system combined with P&O, PSO, ANN, and SVM. The hybrid algorithms have the strengths to provide improved performance in dynamic environmental changes. For grid stability ESS integration is crucial. ESS control and energy management are very attractive areas for research. In renewable energy landscape, smart grid and IoT based technologies are crucial for real time monitoring, power optimization, energy management, control and operations are very big research areas.

According to findings there are some recommendations for researchers, engineers, and policymakers for renewable energy systems.

1. For maximizing power with environmental changes ANN or Fuzzy Logic MPPT algorithms are recommended. Those MPPT gives better performance compared to others. Lost effective and small solar home system applications P&O or PCM will be better, while grid connected system ANN or Fuzzy Logic MPPT
2. Energy demand and forecasting models are essential for optimizing the SHMs components sizing and control system design. MATLAB/Simulink tools can help to simulate and analyze technical issues.
3. To implement hybrid microgrid system economic viability and local policy analysis is essential.

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