A UNIFIED FRAMEWORK FOR MULTI-LEVEL CONTROL AND MULTI-OBJECTIVE OPTIMIZATION OF HYBRID CAMPUS MICROGRIDS: INTEGRATING ADAPTIVE MPC, MODIFIED FIREFLY ALGORITHM, AND HOMER SIMULATIONS

by

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To my parents, siblings, daughter Rateel, nephews, and nieces.

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Edrees Yahya Alhawsawi

ABSTRACT

A UNIFIED FRAMEWORK FOR MULTI-LEVEL CONTROL AND MULTI-OBJECTIVE OPTIMIZATION OF HYBRID CAMPUS MICROGRIDS: INTEGRATING ADAPTIVE MPC, MODIFIED FIREFLY ALGORITHM, AND HOMER SIMULATIONS

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Hybrid microgrids have become an essential solution in integrating renewable energy sources into campus energy systems, addressing sustainability, reliability, and energy efficiency challenges. In this dissertation, I explore a comprehensive framework for controlling and optimizing hybrid microgrids, specifically focusing on the combination of solar PV, wind turbines, Combined Heat and Power (CHP) systems, and Battery Storage Systems (BSS) in a university campus setting. Traditional control strategies often fall short when dealing with the dynamic and intermittent nature of these renewable sources, necessitating advanced optimization and control techniques.

To address these limitations, this research first examines the design and operation of hybrid renewable energy systems through a case study at Oakland University, utilizing HOMER software for simulations. This case study demonstrates the effectiveness in balancing key performance indicators, such as Net Present Cost (NPC), Levelized Cost of Energy (LCOE), and environmental impact. The optimized system configuration illustrates how hybrid microgrids can significantly reduce energy costs while enhancing sustainability in campus applications.

Furthermore, I propose a Modified Firefly Algorithm (MFA) to optimize hybrid microgrid operations by solving multi-objective problems, including cost minimization and greenhouse gas emissions reduction. The MFA was specifically adapted to improve the efficiency of energy management systems (EMS) in microgrids by dynamically adjusting the optimization parameters. The algorithm outperformed traditional optimization techniques, offering superior results for complex multi-objective problems in hybrid microgrids.

Additionally, this dissertation develops a multi-level control framework for hybrid microgrids, incorporating Adaptive Model Predictive Control (MPC) communication. The Adaptive MPC leverages predictive modeling to dynamically adjust control actions based on real-time data, optimizing power dispatch across the various energy sources and storage systems. This integration ensures reliable and efficient communication between distributed energy resources, improving system stability and performance under fluctuating conditions.

This research provides valuable insights into the optimization and control of hybrid microgrids, demonstrated through real-world case studies and modified algorithmic approaches. The proposed methodologies cover more efficient, reliable, and sustainable energy systems in campus microgrids, offering a robust framework for future developments in smart grid technologies.

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LIST OF ABBREVIATIONS AND SYMBOLS

ABC	Artificial bee colony
AC	Alternating current
BESS	Battery energy storage system
CHP	Combined heat and power
CO_2	Carbon dioxide
CS	Cuckoo search
DC	Direct current
DE	Differential evolution
DG	Diesel generator
DG	Distributed generation
DSM	Demand side management
EDNSGA-II	Economic dispatch-based non-dominated sorting genetic algorithm II
EMS	Energy management system
ESS	Energy storage system
EVs	Electric vehicles
FA	Firefly algorithm
FC	Full cell

LIST OF ABBREVIATIONS AND SYMBOLS- (continued)

GA	Genetic algorithm
GA	Genetic programming
GE	Geothermal energy
GW	Gigawatts
GWh	Gigawatt-hour
HOMER	Hybrid optimization of multiple energy resources
HPS	Hybrid power systems
HRDS	High-reliability distribution system
IEA	International energy agency
KW	Kilowatts
LCOE	Levelized cost of energy
LSM	LabVIEW simulation model
MILP	Mix integer linear programming
MOPSO	Multi-objective particle swarm optimization
MPC	Model predictive control
MW	Megawatts
NPC	Net present cost
NSGA-II	Non-dominated sorting genetic algorithm II
PSO	Particle swarm optimization

LIST OF ABBREVIATIONS AND SYMBOLS- (continued)

PV	Photovoltaic
RES	Renewable energy sources
SCADA	Supervisory control and data acquisition
TW	Terawatts
WT	Wind turbine

CHAPTER ONE

INTRODUCTION

1.1 Motivation and Challenges

Nowadays, the renewable section in the energy sector is prioritized as part of the global efforts aimed at embracing sustainability. With the threats of climate change and the reduction of conventional energy resources, the adoption of renewable energy systems such as the sun, wind, and water, have now become important for ensuring a balance with the environment. Such energy systems not only ensure a better environment but also enhance economic development and energy security. Importantly, microgrids have come forth as the most effective way of incorporating renewable sources to the local electric grid. They add reliability and decrease energy waste by operating in islanded mode [1]. For university campuses, microgrids are invaluable for achieving energy self-sufficiency while cutting down expenses and supporting the development of novel approaches to renewable energy science [2].

However, achieving efficiency in microgrid operations requires robust optimization strategies. This is where metaheuristic optimization algorithms, such as the Firefly algorithm, come into play. The algorithm represents the behavior of fireflies to find optimal solutions in complex systems [3].Yet, the basic Firefly algorithm can struggle with convergence speed and accuracy, which is why a modified version is needed to enhance its performance in optimizing the microgrid objectives [4].

Without proper control, microgrids can become unstable, leading to energy inefficiencies, outages, and system failures. Effective control ensures that energy generation and consumption remain balanced, preventing power losses and maintaining system resilience [5]. Adaptive Model Predictive Control (MPC) is particularly suitable for microgrid management, as it allows for real-time adjustments to system changes, ensuring optimal performance in dynamic and unpredictable environments [6].

1.2 Dissertation Objectives

The main objective of this research is to review campus microgrids within the context of the modern energy landscape, where the decentralization of power generation and increased use of renewables have highlighted the strategic importance of microgrids in ensuring resilient, sustainable, and cost-effective energy management. The second objective is to size and optimize the microgrid using the HOMER Pro software, which examines technical, economic, and environmental factors affecting the interconnection of renewable energy technologies. This includes integrating various renewable sources and analyzing their performance and economic impacts, aiming to enhance both the energy efficiency and financial viability of the campus microgrid system. Additionally, this objective extends to employing a modified Firefly algorithm for multi-objective optimization, focusing on improving the Net Present Cost (NPC), Levelized Energy Cost (LCOE), reliability, and greenhouse gas (GHG) emissions metrics. This approach leverages dynamic adjustment of the beta parameter in the algorithm, significantly enhancing the optimization process and outperforming traditional methods. The third objective is to control the campus microgrid power using Adaptive MPC. This includes developing a sophisticated control mechanism that adjusts to varying load and generation conditions, thereby ensuring consistent and reliable power supply while maintaining system efficiency and stability.

1.3 Problem Statement

Microgrids require optimization to manage the complex interplay between energy sources and loads, ensuring efficiency amidst fluctuations in renewable generation and demand. Effective optimization addresses energy costs, resource allocation, and environmental impact while maintaining stability. Due to conflicting priorities, such as cost efficiency, reliability, and reducing carbon footprint, multi-objective optimization is essential, allowing the system to adapt without compromising performance. University campuses are ideal for microgrid systems due to diverse energy demands across facilities. A robust control strategy is crucial for integrating renewable energy, ensuring a stable power supply, and managing the complexities of distribution. Without effective control, microgrids risk instability, inefficiency, and higher costs. A reliable system adapts to internal and external changes, maintaining energy security and sustainability for the campus.

1.4 Dissertation Outline

This dissertation is arranged as follows: Chapter II describes an overview of microgrid systems, including their definition, types, applications, and operating principles. Chapter III comprehensively reviews the deployment of microgrids on university campuses, evaluating their reliability, efficiency, and the integration of renewable energies. Chapter IV Advanced Optimization Techniques for Hybrid

Microgrids. Chapter V introduces the MPC and adaptive MPC control approach. Chapter VI presents the simulation results and discussion. Finally, Chapter VII offers the conclusion and future work.

CHAPTER TWO

MICROGRID OVERVIEW

2.1 Renewable Energy

Utility power sources are not a preferred or sustainable solution because they continue to utilize fossil-based power sources, which are expensive and pose a threat to the environment. Therefore, there is a need for a transition towards RESs due to the importance of the following benefits [7]. Renewable sources like wind, solar, geothermal systems, biomass, tidal, and hydroelectricity are lighter, more efficient, highly reliable, low maintenance, and significantly provide lower CO_2 emissions and lower noise [7-9]. Furthermore, RESs are more cost-effective in the long term than conventional resources, will decrease the cost of energy, and meet the needs of loads reliably and sustainably. In addition, RESs can be linked with other energy resources, including Combined Heat and Power systems (CHPs) and distributed generation (DG), to meet the electricity needs and enhance power quality [10, 11]. The benefits associated with every RES differs depending on the conditions of each source. For example, geothermal energy (GE) is deemed to be among the most viable clean, renewable energy resources because it relies on the heat from the earth to power the steam turbines needed in electric power production. Due to the fact that it is not influenced by weather and can be generated at any time of the year, GE reduces the fluctuation of power supply, which is the main drawback of other types of renewable energy, such as wind, hydro, and solar panels [12].

Furthermore, GE can be installed in a vertical plane almost everywhere while occupying less space compared to wind and solar. Therefore, electricity generation by GE, wind, and solar panels requires approximately 404, 1,335, and 2,340 square miles of land surface for 1-GWh power [13]. The area where GE is best installed should be easily accessible since it penetrates into the surface of the earth for hundreds of meters. The cost of generating 1kW through geothermal, wind, and solar power is USD 3,478, USD 1,274, and USD 3,025, respectively [14-16]. At the end of 2022, the total global cumulative installed capacity of wind, solar, and geothermal power was 906 GWh, 710 GWh, and 14.9 GWh, respectively[14]. As a result, due to the high initial costs involved in drilling boreholes and the construction of facilities required to generate power through the GE, power from the GE is relatively costlier compared to wind and solar [17]. Table 1 illustrates a comparison of renewable energy sources [18-28]. In summary, it is evident that geothermal, wind, or solar energy sources bear similar features of clean, renewable energies with minimal environmental footprint. However, there are certain distinctions concerning the access, performance, and costs of installing these systems. Likewise, decision-making on specific renewable energy sources depends on aspects such as geographical location and energy requirements.

Table 2.1 Comparison of renewable energy sources

Aspect	Solar Energy	Wind Turbines	Geothermal Energy
Availability	Depending on the location	Depending on location	Worldwide
Efficiency	22%	20–40%	32%
Maintenance	Regular	Regular	Low
Installation cost	High	Low	High
Environmental impact (Greenhouse gas)	Low impact	Low impact	No impact
Weather conditions	Affected	Affected	Unaffected

2.2 Hybrid Power Systems

2.2.1 Definition

Hybrid Power Systems (HPS) are the systems which use more than one configuration of renewable and/or conventional energy resources for producing energy. For instance, such systems make use of different types of energy generation such as solar, wind or hydro, in order to take about maximum energy from all nature's gifts, thus enhancing efficiency, reliability, and cost efficiency [29]. Hybrid energy systems mainly comprise "clean" energy resources, such as Photovoltaic (PV), Wind turbines (WT), and GE and "conventional" energy resources, such as CHP, DG, and storage systems. Figure 2.1 also illustrates the hybrid power systems. The HPS relies only on one power source to reduce expenses in the system and enhance functionality, hence their wide usage. There are some advantages of HPSs, including supplying electricity to isolated regions at high efficiency and not being influenced by a fixed source, similar to large-scale networks, which can cause power blackouts [30, 31]. Moreover, through the HPS, fuel costs for consumers are lowered while line losses and disruptions are kept to a minimum [32]. Improvement of the HPS reduces the emission of pollutants and greenhouse gases [33].

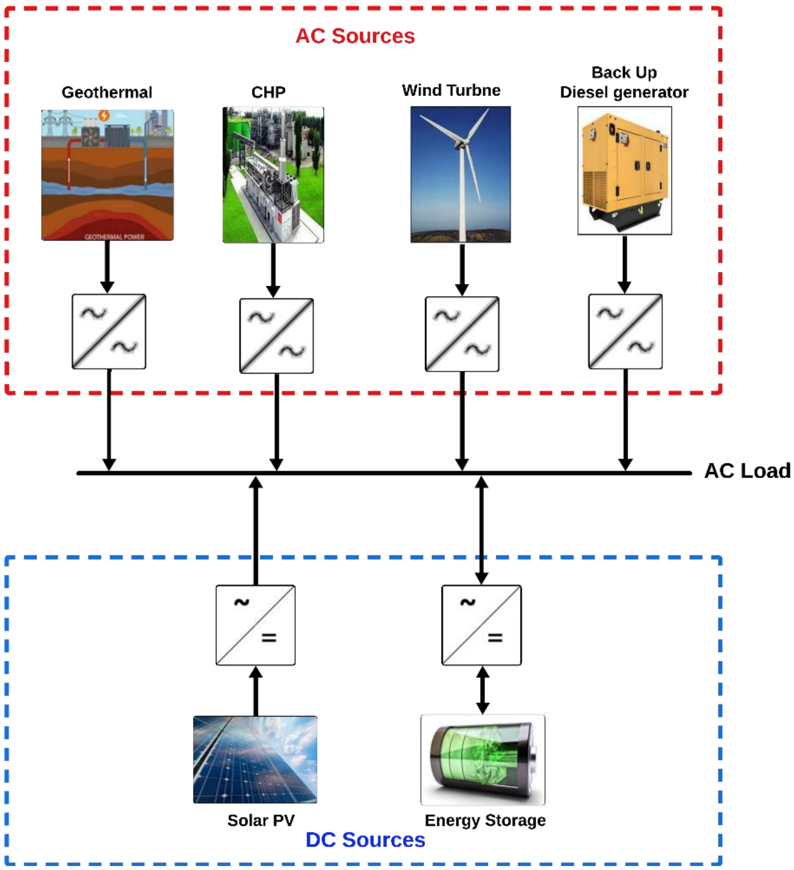

Figure 2.1 Hybrid power system [2]

2.3 Microgrid

2.3.1 Definition

A microgrid is an independent power network that can be interconnected with the main electric network or function as an isolated power source for facilities and complexes, including university campuses, commercial facilities, and hospitals. The islanded system is not synchronously connected to the main grid. However, the grid-connected system is connected to the primary grid. Figure 2.2 depicts the microgrid architecture. Lubna et al. [11] also said that the microgrid system is ideal in regions with weak power transmission, such as isolated villages where an islanded microgrid is the best type of power network in the region. It is crucial to understand that microgrids offer a more reliable and secure energy supply as energy supply becomes vulnerable to natural disasters and cyber threats [34-36]. In addition, microgrids are similar to conventional power grids in terms of control, distribution, transmission, and power generation. Conversely, the microgrid system is unlike traditional grids that can be integrated close to the loads, thus reducing the capital cost of the transmission lines between power generation and consumption cycles.

Microgrid systems offer effective solutions for industrial complexes, commercial areas, residential zones, and university campuses by meeting increasing power demands, improving energy reliability, and reducing utility costs. These systems allow for decentralized energy management, enabling each sector to operate independently during power outages or grid failures. For industrial complexes, microgrids ensure uninterrupted production processes, while in commercial areas and residential zones, they enhance energy efficiency and reduce dependency on the main grid. On university campuses, microgrids support both sustainability goals and energy resilience, making them crucial for academic institutions with significant energy requirements. Additionally, the integration of renewable energy sources into microgrid systems further reduces environmental impact and promotes long-term cost savings across all sectors [37-39].

Figure 2.2 Microgrid architecture [2]

2.3.1 Microgrid Types

Microgrids come in various configurations, with two primary types being grid-connected microgrids and islanded microgrids.

2.3.1.1 Grid-Connected Microgrids: Integration with the Main Grid

Grid-connected microgrids are integrated into the main power grid, allowing for a seamless exchange of electricity with the central utility. These microgrids utilize a combination of renewable energy sources, such as solar panels, wind turbines, and batteries for energy storage [40, 41]. The integration of power electronics and energy storage technologies in these hybrid microgrids presents additional challenges, which are addressed through advanced control systems and modeling techniques [42].

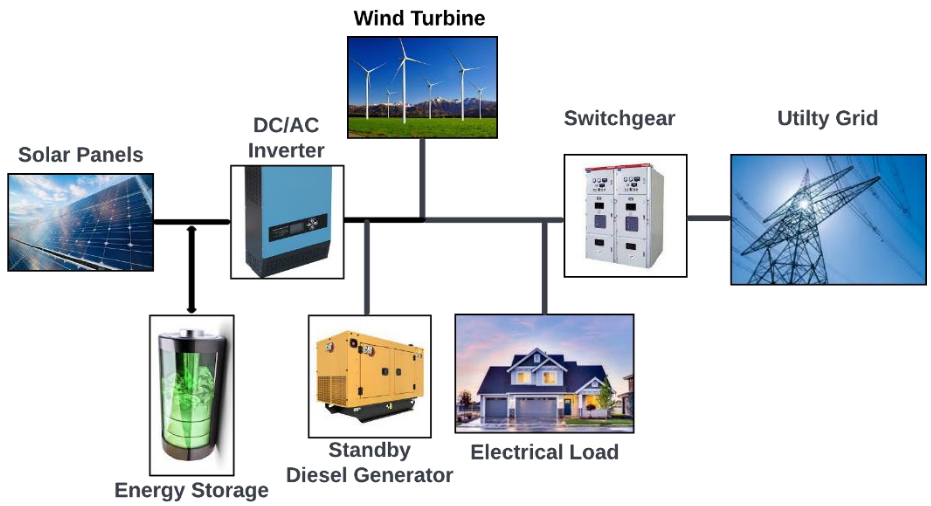

Figure 2.3 Grid-connected microgrid

To ensure the safe connection of renewable energy sources and maintain grid stability during faults, protection devices, such as modified thyristor-based Fault Current Limiters (FCL) with Mutual Inductance FCL integration are proposed [42, 43]. These devices protect converters from transient over voltages and ensure a reliable connection to the utility grid. Overall, grid-connected microgrids with renewable energy sources offer a promising solution for sustainable and resilient power systems. Figure 2.3 illustrates the Grid-connected microgrid.

2.3.1.2 Islanded Microgrids: Independent Operation from the Main Grid

An islanded microgrid is a cluster of renewable and traditional energy sources operating in islanded mode. Islanded microgrids have become a new trend in power grid construction due to the growth of distributed power and advancements in energy storage technology [43, 44]. They are often used in remote areas or on islands where it is difficult to supply electricity from the main grid [45]. These microgrids aim to integrate renewable energy sources (RES) and energy storage systems (ESS) to provide stable power to consumers [46]. Various optimization models and control schemes have been proposed to address the volatility and uncertainty of renewable energy power output [47]. Figure 2.4 shows the Islanded microgrid.

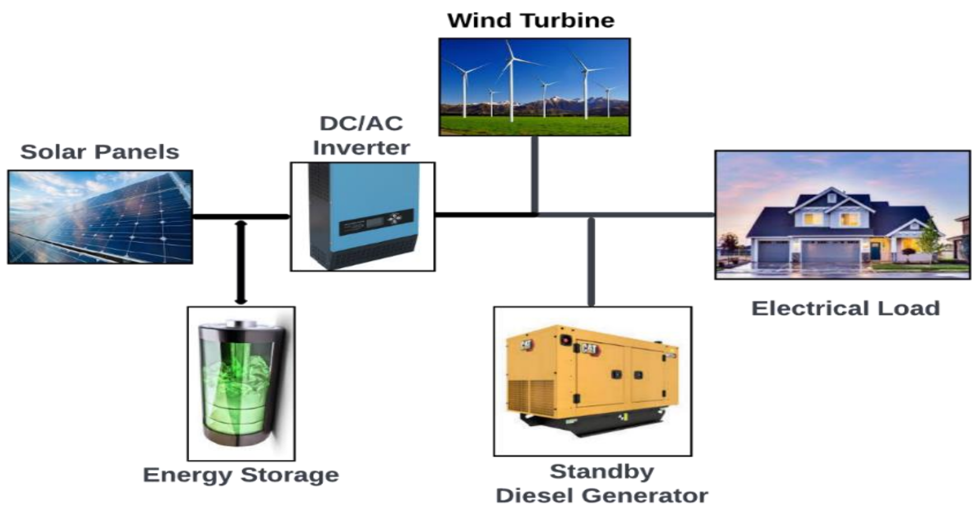

Figure 2.4 Islanded microgrid

2.3.2 Microgrid History

Microgrid studies began to attract attention in the early 2000s, and this was largely as a result of the perceived need for better and more integrated energy supply systems. The concept of microgrids originated in integrating distributed energy resources, or DERs, consisting of solar PVs, wind turbines, and particularly the CHP systems in confined power. Such systems were first researched in order to improve energy supply in isolated areas and for off grid applications including critical facilities, like hospitals and military structures. Microgrids in their early progress are intended to function within an island mode or autonomously from the main grid when the power grid is disconnected, which was important for regions prone to disasters [48].

In the last few years, microgrid investigation has grown in leaps and bounds, particularly with the evolution of renewable energy technologies and energy storage systems. In 2010, microgrids were developed as platforms for incorporating renewables within the existing energy systems by the universities and research institutions. The development of smart grid technologies, real-time data analytic, and advanced control systems have made it possible for microgrids to function more efficiently in grid connected and islanded modes [49].

Optimization strategies have also been researched and developed, such as the multi-objective algorithms, dismissal of which would imply limitations on microgrid operation complexities, cost effectiveness, and reliability criteria [50]. As a consequence, microgrids have become a focal area in efforts to realize transformation of energy systems toward carbon free and resilient systems, including the global undertaking of carbon mitigation and energy independence.

2.3.4 Microgrid Components

The microgrid system has three main components: distributed generation, energy storage system, and loads. The components of the microgrid are represented in Figure 3.

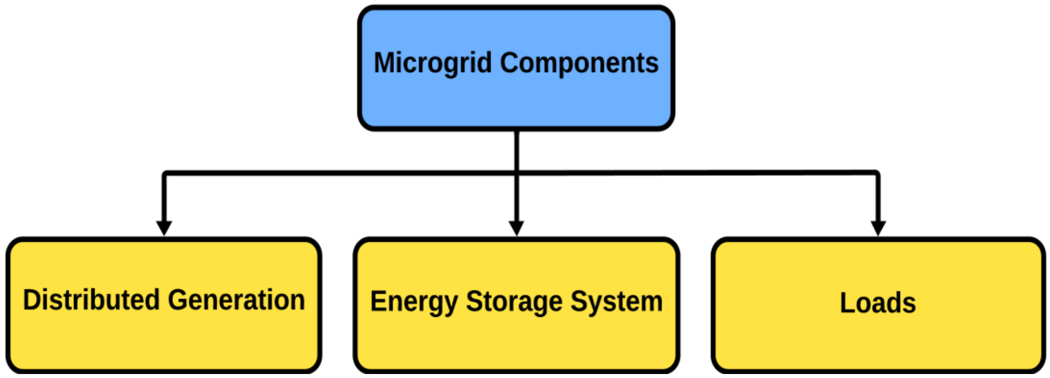

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Figure 2.5 Microgrid components [2]

2.3.4.1 Distributed Generation

Distributed generation (DG) describes the use of power generation techniques that produce power locally close to the building rather than relying on a central power plant. The forms of energy that can be employed by DG are either conventional energy systems, such as fuel cells (FCs), diesel, nuclear, and natural gas, or renewable energy systems, like wind turbines (WT), biogas, geothermal energy (GE), and photovoltaic solar energy (PV) [51]. Some DG types can generate CHP since they employ heat, and part of the waste heat is produced by the energy source. Secondly, the DG can also save energy expenses and lessen the emission of greenhouse gases. As a result, this can significantly improve the overall efficiency of the DG unit. Certain distributed generation systems call for a power electronics device, such as an AC/DC converter, that assists in converting the harvested energy to that of the utility grid. Distributed generation renewable sources are commonly used for electricity generation. Wind energy has seen a good amount of installed capacity in the last decade, with a cumulative installed capacity of almost 900 GW by the end of 2022 [52].

In addition to solar PV energy, TW energy has emerged as a paramount microgrid resource. The global level installed capacities for PV, WT, and GE are expected to be 2,000 gigawatts, 1 terawatt, and 234,368, megawatts, respectively, by 2030 [7, 53, 54]. Furthermore, the International Energy Agency (IEA) predicted that more additions will also come from renewable energy sources compared to all types of fossil energy sources annually for the next decade [55]. Therefore, to ensure that distributed power generation using renewable energy sources has the required capability to meet the user's needs or requirements, the system must be aligned with the user. There are two factors, namely the demand-to-coverage ratio and the self-consumption ratio, which should be taken into consideration [56, 57]. Figure 2.6 represents the distributed generation system.

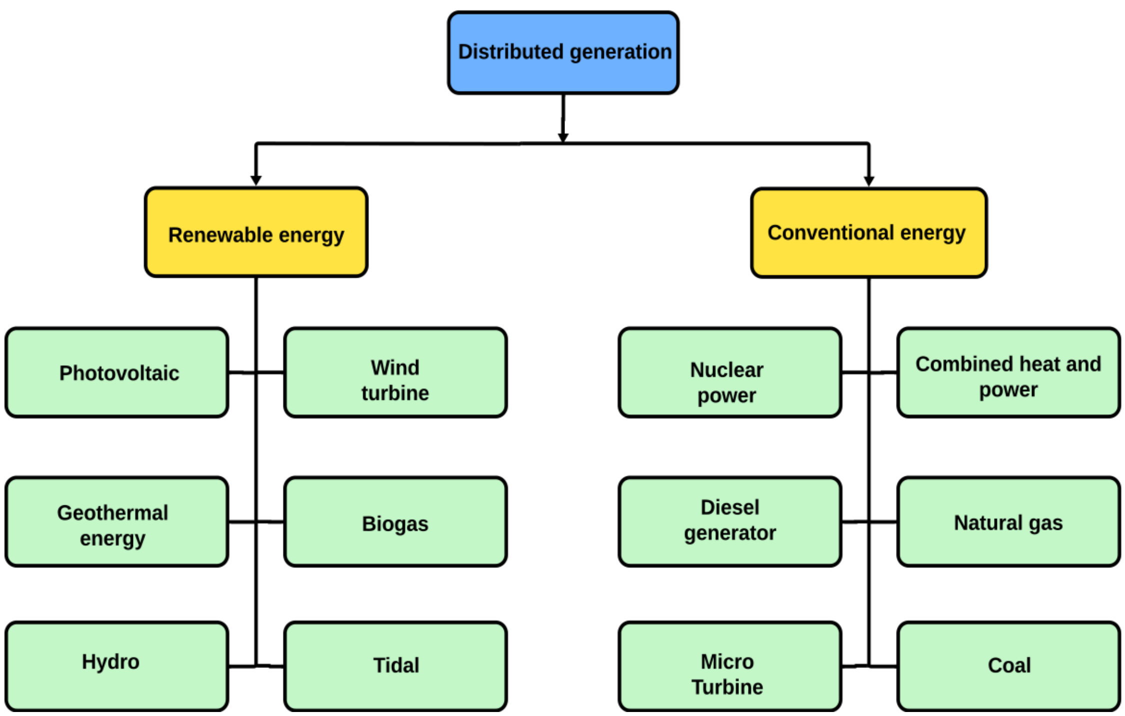

Figure 2.6 Distributed generation system [2]

2.3.4.2 Energy Storage System

An energy storage system (ESS) is a system that allows for storing energy derived from renewable and non-renewable sources in a reserve. This power can then be used for a range of useful purposes (e. g., homes, air conditioning, electronics, automobiles, etc.) [58]. Since energy production and consumption are not equal because of various factors like energy requirements, climatic conditions, etc., the ESS provides the best answer to the energy supply-demand disparity. Other benefits of an ESS include the enhancement of the environment, reduction of outages, and provision for the incorporation of varied resources [59]. The energy that has been captured and utilized can be picked up in electrochemical, thermal, hybrid, chemical, mechanical, and electrical forms [60]. This is the energy storage system classification, as depicted in Figure 2.7. Various standards of ESS components should be taken into consideration during microgrid design, including equality of energy needs and power supply. The biggest storage of energy capacity should be stored during the nights or other periods of low energy consumption while delivering the energy as required. Moreover, the transient conditions are maintained smooth when the microgrid changes from islanded mode to grid-connected mode and vice versa [10].

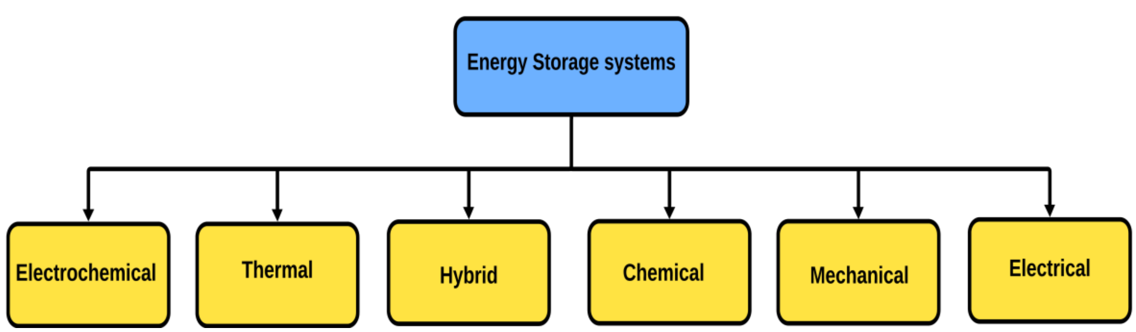

Figure 2.7 Classification of energy storage systems [2]

For a complete list of current energy storage systems, see table A-1 Appendix A

2.3.4.3 Microgrid Loads

Microgrids possess several load types that are essential to their functionality, stability, and control. In addition, the microgrid can provide power to several residential/campus/commercial loads and also meet the power requirements of sensitive/critical loads that require high reliability. Figure 2.8 describes the load types in microgrids. Some of the issues that should be addressed include load prioritization, improvement of power quality and reliability for selected loads, and load reliability for pre-selected loads. Moreover, local generation is an insurance policy against disruption as it involves faster protection measures with high precision [51, 61].

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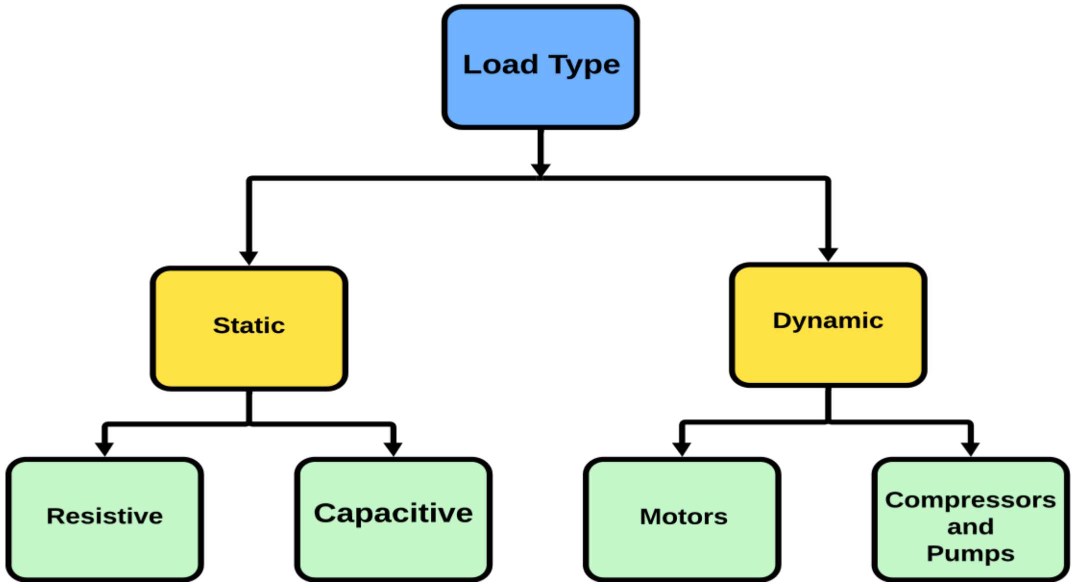


Figure 2.8 Microgrid load types [2]

CHAPTER THREE

MICROGRID ARCHITECTURE FOR UNIVERSITY CAMPUSES

3.1 Introduction

University campuses are increasingly utilizing microgrid systems in order to overcome the limitations associated with traditional utility power and fossil fuel use. Renewable energy sources, including solar and wind energy, are usually utilized to supplement a hybrid power system that utilizes alternative energy, as well as traditional energy sources to provide campus energy services.

There are several configurations of microgrid systems, including grid-connected microgrids, which are investigated as options for energy solutions that are both reliable and flexible. During this study, the costs, performance, efficiency and impact of integrating renewable energy sources are discussed. Additionally, microgrids are also considered as a solution for reducing costs, improving energy reliability and promoting sustainable development in and around universities.

3.2 Campus Microgrid Overview

University campuses consume a large amount of electricity, and therefore, it is inconvenient to rely only on the utility grid. As a result, hybrid energy sources can be viewed as the best option to decrease the cost of operating campuses. Hence, several universities have adopted microgrids that draw from multiple sources, such as photovoltaic (PV), wind turbines (WT), geothermal energy (GE), combined heat and power (CHP), and diesel generators (DGs). The probability of installing renewable energy sources like batteries is likely to be influenced by factors like meteorology and the size of the campus. The following campuses have installed various renewable and conventional power resources.

3.2.1 Oakland University

Oakland University in Rochester, Michigan, USA, integrated hybrid geothermal, photovoltaic, solar thermal, and cogeneration heat and power energies [62-66]. The authors in [1] proposed an economical integrated renewable generation system of PV, ESS, and WT for microgrid application and conducted performance and efficiency evaluation via HOMER software (V3.14.5). Figure 3.1 is an illustrated representation of a microgrid at Oakland University. This study revealed that there exists an opportunity to achieve effective economic and environmental energy solutions.

Figure 3.1 Oakland University microgrid [67]

3.2.2 Illinois Institute of Technology

The Illinois Institute of Technology, located in Chicago, Illinois, USA employed distributed generation (DG), controllable loads, storage, and switches. This study used a high-reliability distribution system optimization technique to obtain high operations cost-efficiency results. The total annual operating costs decreased from USD 140,497 to USD 126,644 per year, about 9% [68]. This shows how the energy management system helped reduce operational costs noticeably while boosting energy usage efficiency. In Figure 3.2, the original microgrid of the Illinois Institute of Technology is depicted.

Figure 3.2 Microgrid at the Illinois Institute of Technology [69]

3.2.4 The University of Coimbra

The University of Coimbra in Coimbra, Portugal has adopted an innovative energy system for PV plants, lithium-ion batteries, electric vehicles, and intelligent controllers.

The system’s performance and efficiency were assessed using the Laboratory Virtual Instrument Engineering Workbench (LabVIEW). In this analysis, it was found that the energy system introduced at the university helped reduce energy consumption and met 22.3% of the campus’ annual electricity consumption. The actual microgrid at the University of Coimbra is depicted in Figure 3.4. It is evident that the system is committed to sustainable energy and has the capacity to meet a considerable part of its energy demands. The annual energy generation of one unit is 115. 6 MWh per year, while the specific energy yield is 1,466 MWh per year. It was found that the PV system’s energy ratio between the theoretical and the actual energy efficiency was 88, while the amount of energy fed into the grid was 6.5 MWH within it is total 109 MWH [70].

Figure 3.4 Microgrid at the University of Coimbra [71]

3.2.7 University of California

The University of California, San Diego (UCSD), in San Diego, CA, USA has installed a microgrid system that provides electrical, heating, and cooling services for a 450-hectare campus accommodating a daily population of 45,000. Comprising two 13.5 MW gas turbines, a 3 MW steam turbine, and a 1.2 MW solar-cell array, this system collectively caters to 85% of the campus's electricity demand and 95% coverage for heating and cooling needs. Noteworthy is the environmental efficiency of the turbines, emitting 75% fewer criteria pollutants than a standard gas power plant. The heating, ventilation, and air conditioning (HVAC) system incorporates a 140,674 kW/h thermal energy storage bank with a capacity of 14,385 m^3, complemented by three steam turbine-driven chillers and five electricity-driven chillers. Additionally, UC-San Diego's self-generation sponsored a 2.8 MW molten carbonate fuel cell utilizing waste methane. Figure 3.7 shows solar panels in the microgrid at the University of California, San Diego. The campus connects to San Diego Gas and Electric (SDG&E) through a single 69 kV substation, employing a straight supervisory control and data acquisition (SCADA) system for seamless communication between building systems and energy supply. UCSD is currently integrating an advanced master controller (Paladin) to oversee generation, storage, and loads. Operated with hourly computing for optimal conditions, Paladin can process up to 260,000 data inputs per second. Supporting Paladin is the VPower software, which analyzes market-price signals, weather forecasts, and resource availability. Monitoring is facilitated by approximately 200 power meters on main lines and at building main circuit breakers, tracking usage on a minute-by-minute basis [72].

Figure 3.7 Solar panels in the microgrid at UCSD [72]

3.2.9 Princeton University

The primary constituent of the microgrid at Princeton University in Princeton, New Jersey, USA, installed is a 15 MW gas turbine, which is augmented by 4.5 MW of PV power. During Hurricane Sandy, Princeton's gas-powered CHP facility supplied electricity, heating, and ventilation, ensuring the university's operations continued despite the widespread outages that engulfed most of the state. The microgrid at Princeton is typically linked to the local grid for operation [73]. Figure 3.9 illustrates Princeton University's CHP plant microgrid.

Figure 3.9 Princeton University's CHP plant microgrid [74]

3.2.10 Nanyang Technological University

Nanyang Technological University in Singapore, Singapore has implemented a cutting-edge Microgrid Energy Management System (MG-EMS). This system comprises PV panels, FC, and natural gas-operated micro-turbines (MTs), all integrated under the Laboratory of Clean Energy Research (LaCER) [75]. Figure 3.12 illustrates the microgrid at Nanyang Technological University. This system's focus extends to buildings and transportation within the campus, showcasing NTU's commitment to sustainable energy practices. By incorporating various clean energy sources and advanced management systems, Nanyang Technological University stands at the forefront of energy research and application, particularly in academic institutions.

Figure 3.12 Microgrid at Nanyang Technological University [76]

For a complete list of current and pending campuses exploring various microgrid configurations, see Table A-2 in Appendix A.

3.3 Campus Microgrid Architectures

Campus microgrids typically comprise photovoltaic cells, wind turbines, combined heat and power systems, and energy storage systems. It is essential that these variables are considered when determining how these components will be configured within the microgrid. These variables are also crucial in determining the performance and efficiency of the microgrid system. Depending on campus requirements, microgrid components can be configured differently, thus allowing a number of design options. Microgrid construction types are generally categorized into the following categories:

3.3.1 Configuration A: (Hybrid PV-Grid-Connected)

There are several components to the system shown in Figure 3.13, including the utility grid, photovoltaic panels, converters, inverters, and energy storage. Photovoltaic panels are the main source of renewable energy used in generating electricity. In order to use the output direct current (DC) produced by the photovoltaic (PV) panels in electrical devices, converter inverters are required. The campus buildings are kept connected to electricity by diesel generators during blackouts.

The advantages of a hybrid PV-grid connection are that it is simple, free to operate, and sometimes does not require energy storage, such as when solar power generates less electricity than the campus demands. However, on the other hand, PV panels are influenced by weather conditions, which could limit their ability to generate power. Moreover, the hybrid PV-grid-connected system is commonly installed in residential and commercial buildings due to its simplicity. For instance, many university campuses worldwide have installed hybrid PV-grid-connected systems, such as the University of Energy and Natural Resources [77], GITAM Deemed To be University in Andhra Pradesh [78], University Malaysia Pahang [79], Effat University [80], Heriot-Watt University [81], Chiba University of Commerce [82], The Hashemite University [83], University at Albany [84], Aga Khan University [85], Colorado State University[86], University of Northern Colorado [87], University of Wisconsin [88], Iowa State University [89], University of Nottingham, Bath University, Exeter University and University of the West of England [90], and Washington and Lee University [91].
It is important to note that the required energy storage system (ESS) depends on the amount of solar capacity installed on the campus. When the power produced by the PV

panels exceeds the consumption demand, an energy storage system is required. For example, the University of Texas [92], British Malaysian Institute [93], Mulhouse campus [94], North Central College [95], Gavilan College [96], Sanford Burnham Prebys Campus [97], New Mexico State University [98], and California State University [99]. Other university campuses such as Beloit College, Fairleigh Dickenson University, Georgia Tech, Lake Superior College, Lane Community College, Luther College, Northern Arizona University, Milwaukee Area Technical College, South Central College, Thomas College, Tuskegee University, University of California Riverside, University of Colorado–Colorado Springs, University of Minnesota Duluth, and Washington and Lee University are suitable for installing solar power and energy storage systems owing to their weather conditions and geographical locations according to the National Renewable Energy Laboratory [100].

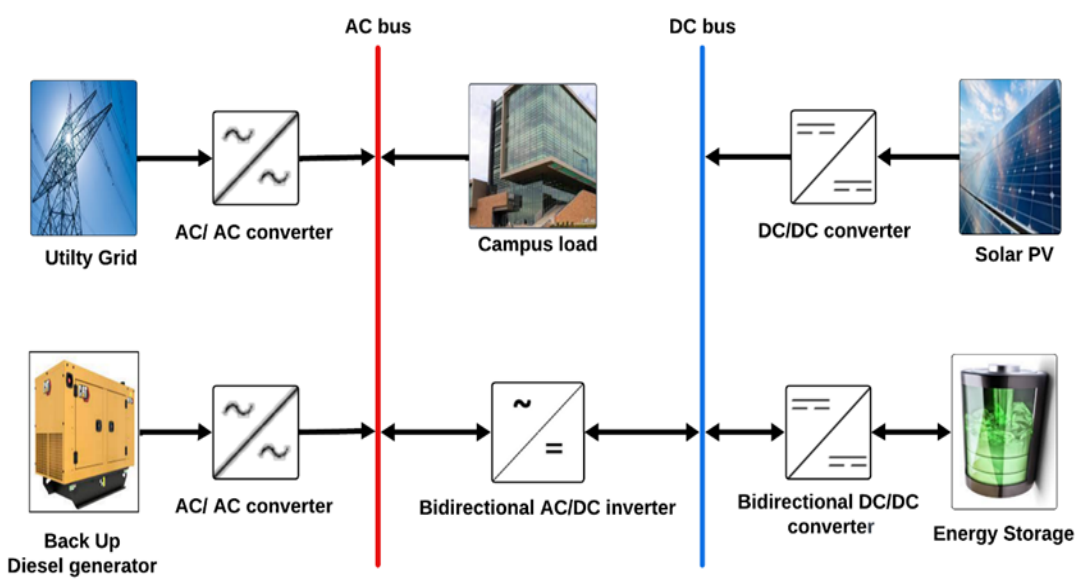


Figure 3.13 Grid connected with solar PV and energy storage [2]

3.3.2 Configuration B (Hybrid PV-WT-Grid-Connected)

An essential component of this hybrid configuration is photovoltaic panels, wind turbines, a utility grid, converters, and inverters. Among the components of this configuration, wind turbines and PV panels are considered the primary sources of renewable energy; figure 3.14 illustrates these components. It is estimated that wind turbines are capable of being installed in three different ways: distributed wind (small turbines on sites), land-based wind (farms and forests), and offshore wind (oceanic waters) [101]. Since wind generators work best in an isolated environment, few universities have installed wind turbines, such as Quinnipiac University [102], the University of Delaware [103], Carleton College, the University of Minnesota [104], St. Olaf College [105], and Macalester College, St. Paul [106].

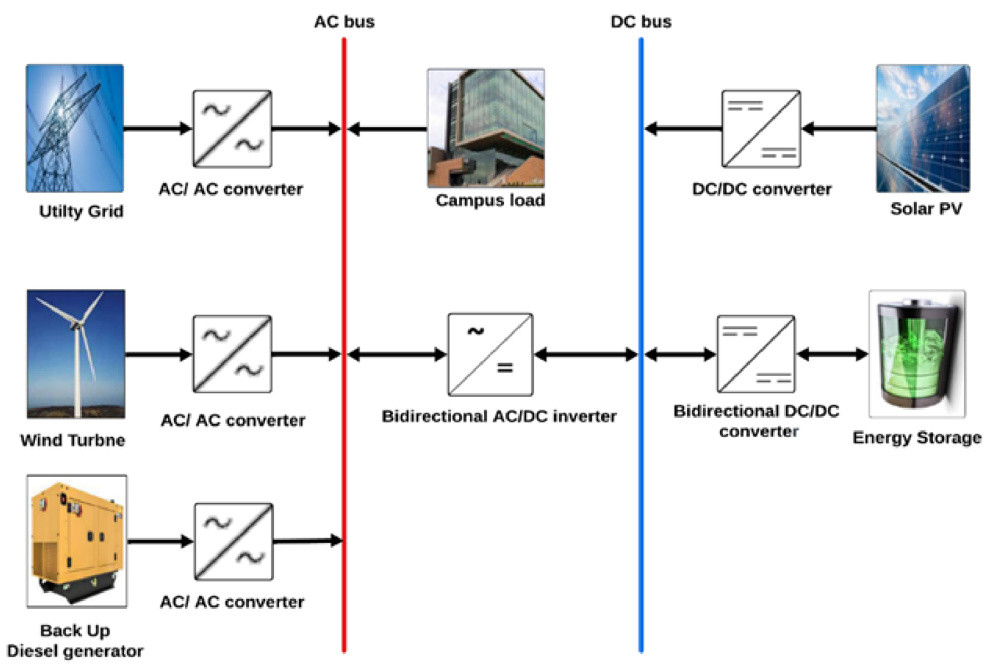


Figure 3.14 Microgrid connected with solar PV, WT, and ESS

3.3.3 Configuration C (Hybrid PV-Diesel Generator-Grid Connected)

A hybrid power system has a PV, DG, and grid connection, similar to that shown in Figure 20. This configuration has been installed at the following universities: Florida International University [107], the University of the Free State [108], the University of KwaZulu Natal [8], and the Jomo Kenyatta University of Agriculture and Technology [109].

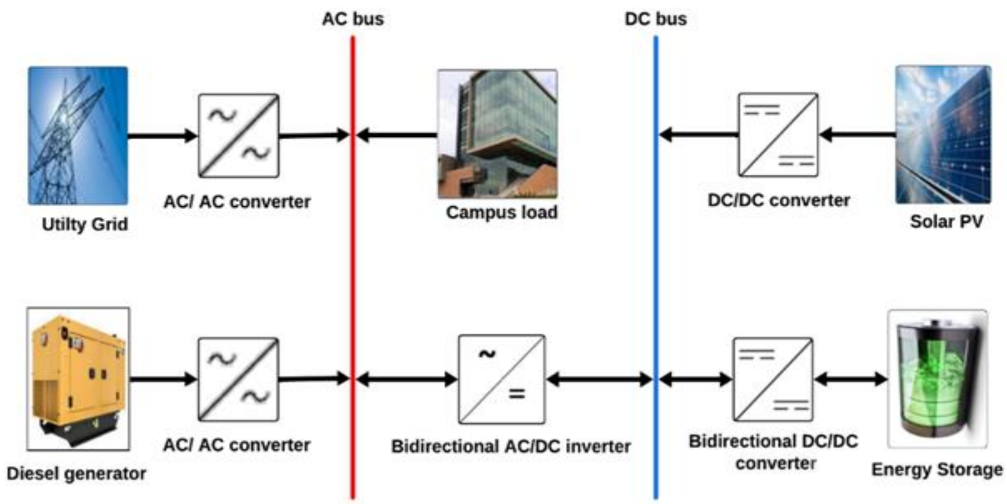


Figure 3.14 Grid connected with PV, diesel generator, and energy storage [2]

3.3.3 Configuration D (Hybrid PV-CHP-Grid Connected)

A hybrid system composed of a solar panel, a gas turbine, a converter, and an inverter are illustrated in this configuration. A CHP allows both electricity and heat to be produced simultaneously, which is more efficient than producing them separately [110]. In addition to their distinctive characteristics, microgrids have a greater ability to utilize renewable energy and heat-power generation [111] and thus are more adaptable than centralized grids. An illustration of this configuration is provided in Figure 3.15.

The following universities have installed this configuration, including Oakland University [1], the University of West of England [112], Kent State University [113], Chalmers University of Technology [114], Stanford University [115], Clemson University [116], and the University of Genoa [117].

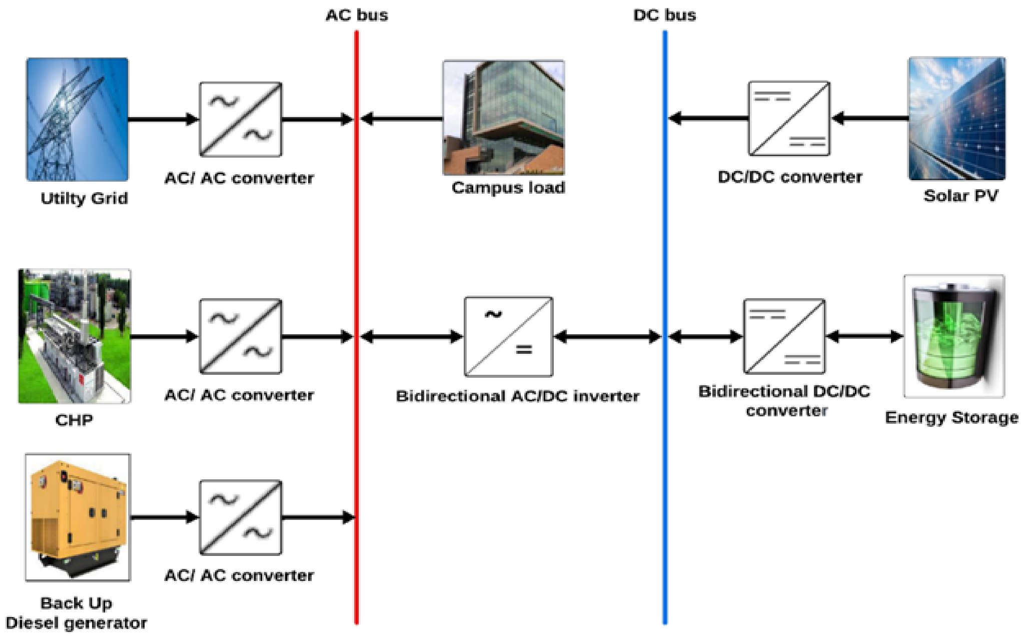


Figure 3.15 Microgrid connected with PV, CHP, and ESS

CHAPTER FOUR

ADVANCED OPTIMIZATION TECHNIQUES FOR HYBRID MICROGRIDS

4.1 Optimizing Hybrid Microgrids with the Modified Firefly Algorithm

A hybrid microgrid system is studied using a focus on the connection between renewable energy sources, such as wind, and conventional power generation. Hybrid microgrids can also boast advantages of hybrid energy sources, but the variability of the renewable energy makes the operation management of the hybrid microgrid a multi-objective optimization problem. Most optimization techniques are mainly ineffective in dealing with trade-offs among competing objectives including cost, energy assurance, and environmental issues.

As a solution to this problem, this research proposes a Modified Firefly Algorithm to facilitate hybrid microgrid optimization. The proposed algorithm is able to dynamically present an overall approach for addressing the various objectives related to microgrid optimization by aiming at increasing the proportion of renewable energy usage effectively without compromising energy storage and generation management. Furthermore, this chapter presents the challenges in stabilizing electricity supply, the need to manage the intermittence of renewable energy, and the need to be practical in the design solutions through operational limitations. The findings enhance understanding of how hybrid microgrids can be operationalized with a focus on reliability and cost effectiveness, fostering the development of improved energy systems for organizations and communities.

4.1.1 Optimization Techniques in Microgrids: From Single-Objective to Multi-Objective Approaches

Optimization is a key aspect of microgrid design, particularly when managing hybrid renewable energy systems. Single-objective optimization algorithms, such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Simulated Annealing (SA), are commonly used to optimize specific goals like minimizing costs or maximizing energy efficiency [118]. These algorithms focus on improving one aspect of the microgrid, such as minimizing the Net Present Cost (NPC) or reducing energy consumption, and have been widely applied in both academic and industrial research [119]. For example, a study by Khenissi et al. [120] applied GA and PSO to optimize the operation of a solar PV-based microgrid, reducing energy costs while ensuring continuous supply.

GA is particularly effective in solving complex optimization problems by simulating the process of natural selection. It has been successfully applied in microgrid optimization to reduce operational costs and improve energy efficiency [121]. PSO, on the other hand, is inspired by the social behavior of birds and fish and excels in finding optimal solutions quickly, making it ideal for real-time microgrid management [122]. Simulated Annealing is another popular method, known for its ability to escape local optima and converge toward global solutions in complex systems [123].

However, single-objective optimization often fails to capture the multi-dimensional nature of microgrids, where multiple conflicting objectives, such as cost, reliability, and environmental impact, must be balanced. To address this, multi-objective optimization techniques have gained traction in recent years. Algorithms like Non-dominated Sorting

Genetic Algorithm II (NSGA-II) and Multi-Objective Particle Swarm Optimization (MOPSO) allow researchers to optimize several objectives simultaneously, providing a set of Pareto-optimal solutions that offer trade-offs between different goals [124].

For instance, multi-objective optimization can help design microgrids that minimize both costs and greenhouse gas emissions while ensuring reliable energy supply. A study by Zhang et al. [125] applied a Multi-Objective Particle Swarm Optimization (MOPSO) technique to optimize hybrid microgrids, successfully balancing cost reduction with environmental impact mitigation by finding a Pareto-optimal solution that accounts for both economic and ecological objectives. Furthermore, Khan et al. [126] explored how multi-objective optimization techniques can be applied to integrate renewable energy sources more effectively, resulting in improved energy stability, reduced emissions, and cost-efficiency. By exploring the trade-offs between these objectives, decision-makers can select configurations that align with their institution's priorities, whether it be cost savings, sustainability, or energy independence [127]. These multi-objective approaches are particularly beneficial in microgrids, where balancing economic, environmental, and technical performance is crucial [128].

4.1.2 The Basic Firefly Algorithm

The Firefly Algorithm (FA), developed by Yang, is a metaheuristic algorithm inspired by swarm intelligence [3]. It represents an innovative approach rooted in ecological intelligence, designed to address complex optimization challenges [129, 130]. This search algorithm draws inspiration from firefly social interactions and bioluminescent communication. Two key aspects of FA are the definition of attractiveness and the adjustment of light intensity [131]. This algorithm emulates the social interactions of fireflies as they move through the tropical summer sky. Fireflies use flashing patterns to communicate, search for targets, and attract other fireflies, particularly those of the opposite sex.

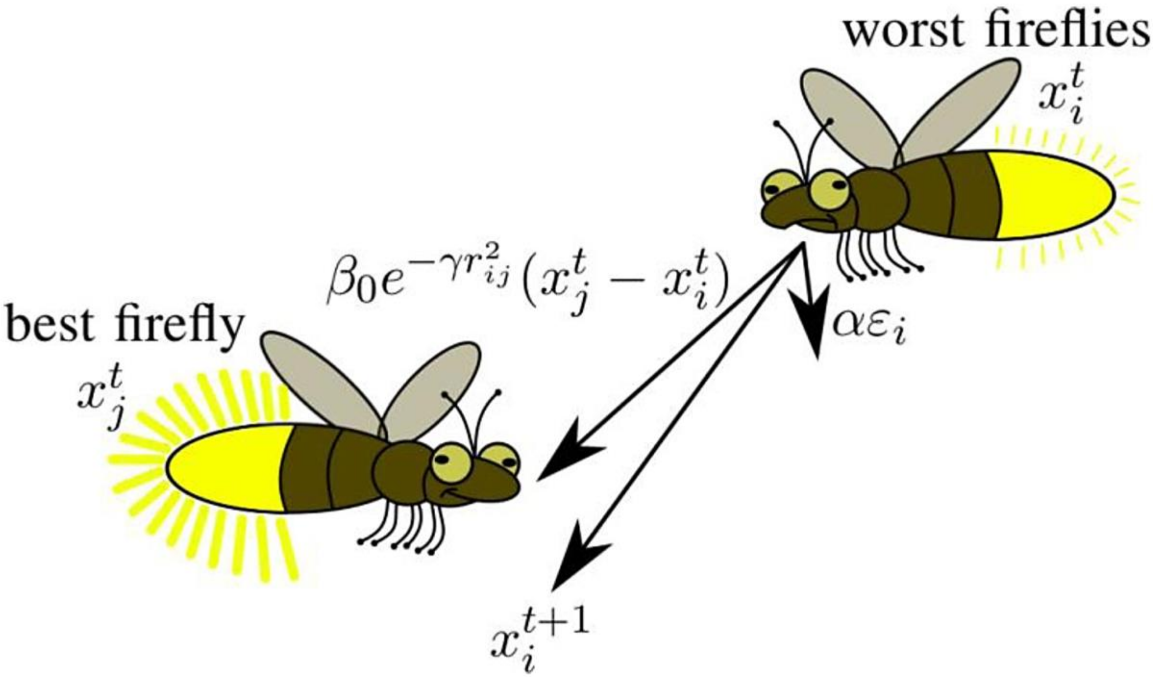


Figure 4.1 Basic Mechanism of the Firefly Algorithm [132]

Natural behaviors can be emulated to create metaheuristic algorithms inspired by nature. To streamline the design of a firefly-inspired algorithm, certain characteristics of fireflies' flashing are idealized, resulting in three simplified rules. First, all fireflies are considered the same sex, ensuring that each firefly can be attracted to any other, regardless of anatomy. Second, a firefly's brightness is directly correlated with its attraction, and brightness decreases with increasing firefly distance. For any pair of flashing fireflies, the dimmer one will move towards the brighter one. If any brighter fireflies do not surround a firefly, it will move randomly within the search space. Third, the objective function influences or determines a firefly's brightness.

The brightness in the optimization problem is very similar to the value of the cost function. Analogous to the fitness function in the PSO algorithm, different types of brightness can also be defined. The FA updates the formula for every firefly pair; the position of a firefly i moving towards a brighter firefly j is given by [133]:

$$x_i^{(t+1)} = x_i^{(t)} + \beta_0 e^{-\gamma r_{ij}^2} \left(x_j^{(t)} - x_i^{(t)} \right) + \alpha \epsilon_i^{(t)} \tag{4.1}$$

Where: x_i an x_j are the positions of the Fireflies i and j, β_0 : the initial attractiveness, γ: the light absorption coefficient, r_{ij}: the distance between Fireflies i and j, α: the random movement coefficient, ε_i: the random vector is drawn from a uniform distribution.

4.1.3 Modifying the Firefly Algorithm

The Modified Firefly Algorithm (MFA) is introduced to enhance multi-objective optimization. The MFA procedures are as follows. A dynamic attractiveness coefficient is introduced and adapted based on each firefly's multi-objective performance. This coefficient, $\beta_{ij}(t)$, is designed to account for the Pareto dominance relationship between fireflies (i) and (j), ensuring that fireflies move towards more dominant solutions. The distance calculation is also modified to incorporate a weighted sum of normalized distances for each objective. This modification enhances the distance metric to accurately capture the trade-offs among different objectives, ensuring that movement decisions are based on a comprehensive understanding of the solution space. Ultimately, the integration of an adaptive technique for reducing randomness systematically reduces randomness over time. This strategy is specifically designed for multi-objective optimization, balancing the need to explore the search space with the exploitation of advantageous regions, thereby enhancing the algorithm's efficiency in achieving optimal solutions.

- MFA equations
- Pareto-Based Dynamic Multi-Objective Attractiveness

$$\beta_{ij}(t) = \beta_0 \left(1 + \frac{n_{dom}(j) - n_{dom}(i)}{n_{total}}\right) e^{-\gamma r_{ij}^2} \tag{4.2}$$

Where: $\beta_{ij}(t)$: the dynamic attractiveness based on Pareto dominance, $n_{dom}(j)$: the number of solutions dominated by firefly (j), $n_{dom}(i)$: the number of solutions dominated by firefly (i), n_{total}: the total number of fireflies, r_{ij}: the multi-objective distance calculated using the weighted sum of normalized distances.

- Multi-Objective Distance Calculation

$$r_{ij} = \sqrt{\sum_{k=1}^{M} \omega_k \left(\frac{f_k(x_i) - f_k(x_j)}{f_k^{max} - f_k^{\min}}\right)^2} \tag{4.3}$$

Where: M: the number of objectives, ω_k: the weight assigned to the k-th objective, f_k^{max} and $f_k^{\min}$: are the maximum and minimum values of k-th objective across all fireflies.

- Mechanism Adaptive Randomness Reduction

$$\alpha(t) = \alpha_0 \, exp\left(-\frac{t}{Iter_{max}}\right) \tag{4.4}$$

Where: α_0: the initial random movement coefficient, t: the current iteration numbers, $Iter_{max}$: the maximum number of iterations.

- Update Equation

$$x_i^{(t+1)} = x_i^{(t)} + \beta_{ij}(t)\left(x_j^{(t)} - x_i^{(t)}\right) + \alpha(t)\epsilon_i^{(t)} \tag{4.5}$$

Where: $\beta_{ij}(t)$: incorporates multi-objective attractiveness, $\alpha(t)$: the time-adaptive randomness reduction.

- Pseudo-code

Steps:

1. Initialize the positions x_i (for $i = 1,2, \dots., N$) randomly in the solution space:

- This correctly specifies the initialization of firefly positions.
- Evaluate the light intensity I_i for each firefly based on the objective functions $f_k(x)$:
    - This is correct, as the objective function values determine light intensity.

2. While (termination condition not met):
    - Increment iteration t:
        - This ensures the loop progresses through the specified number of iterations.

For each firefly i from 1 to N:

For each firefly j from 1 to N:

If $I_j > I_i$ (i.e., firefly j is brighter than firefly i):

This correctly checks if firefly j is brighter than firefly j.

Calculate the multi-objective distance r_{ij} between fireflies i and j:

This step is correct; it computes the distance considering all objectives.

Calculate the dynamic attractiveness $\beta_{ij}(t)$

This is correct; it dynamically adjusts attractiveness based on Pareto dominance and the multi-objective distance.

- Move firefly i towards firefly j using the Improved Update Equation, which correctly updates the position of firefly i, considering attractiveness and random movement.

End If

End For (j)

Evaluate the new light intensity $I_i^{(t+1)}$ for firefly i:

This correctly updates the light intensity based on the new position

End For (i)

Reduce the randomness $\alpha(t)$ which is correctly models the decrease in randomness over time.

Sort the fireflies based on their updated light intensity.

Sorting is crucial to determining the best global positions and helps in guiding the search process.

End While

Output:

The best firefly positions (x) and elapsed time: This provides the final solution set and the time taken to reach it.

4.2 Optimal Design and Operation of Hybrid Renewable Energy Systems for Oakland University

A strategic planning and design process is being conducted at Oakland University as part of the restructuring process, using an application known as HOMER Pro, which examines technical, economic, and environmental factors affecting the interconnection of renewable energy technologies. To satisfy the university's energy requirements, the application facilitates the integration of various types of energy resources, including solar panels, energy storage systems, and wind turbines. In addition, this research aims to address the problem of supplying uninterrupted electrical energy to the university within the microgrid system where essential loads are not met. As a result, an hourly load profile of the campus is entered into HOMER Pro over the course of the previous year and its energy setup is modeled and analyzed accurately. This methodology aims to develop a microgrid that can be replicated and modified in order to improve the system without incurring unreasonable costs and/or disruptions.

4.2.1 Hybrid Optimization Model for Electric Renewables (HOMER) Pro

This program works by modeling and assessing the technical feasibility of various configurations of hybrid power systems that are based upon renewable and conventional sources of power. The strength of HOMER Pro is that it can conduct extensive sensitivity analysis that evaluates effects of varying specific input assumptions and conditions [134]. Owing to these reasons, researchers find HOMER Pro extremely useful when it comes to microgrid design, as it is able to conduct detailed and comprehensive economic assessments along with an evaluation of technical parameters that are essential for energy system optimization.

The software's capability to integrate multiple generation sources and to model both technical and financial forecasts makes it an indispensable tool for anyone involved in the planning and deployment of renewable energy systems. Its use is widespread among engineers, designers, and researchers, offering invaluable support in making decisions about the sizes and types of systems to implement, based on quantitative data rather than assumptions [135].

4.2.2 Data Collection for MG Design Simulator

This step involves collecting and analyzing critical data to input into the HOMER Pro software for microgrid (MG) design simulation:

- Solar GHI Resource Statistics

Monthly mean statistics of the solar Global Horizontal Irradiance (GHI) in the state of Michigan are gathered. Figure 1 illustrates the daily radiation and clearness index, showing the quantity of solar energy received daily and the impact of atmospheric conditions on solar reception.

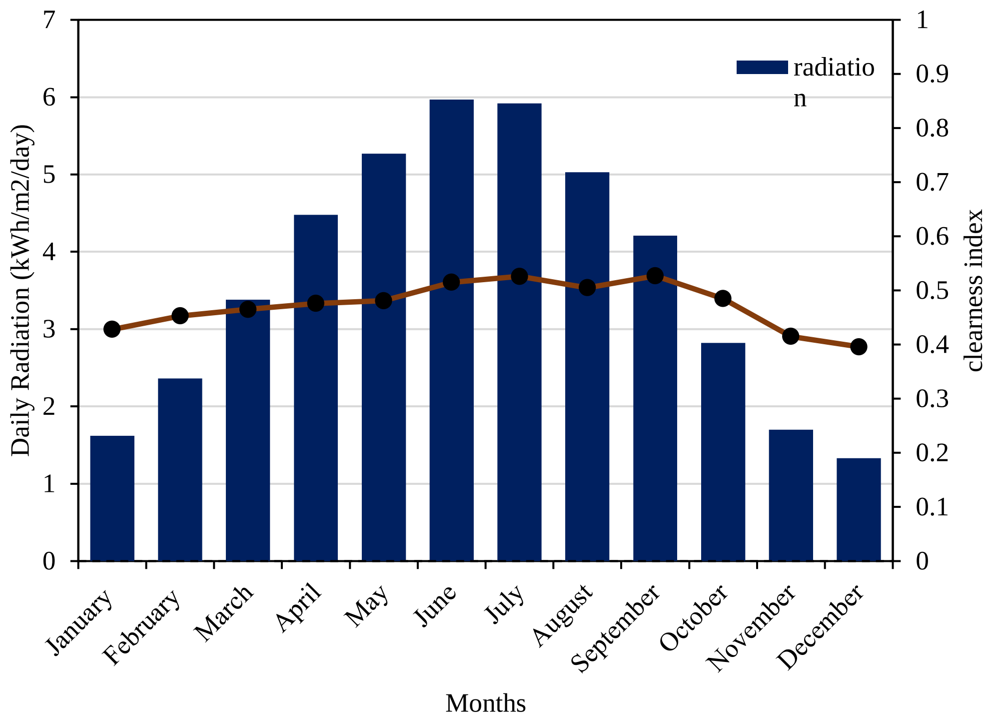


Figure 4.2 Monthly average solar GHI data for the state of Michigan [1]

- Wind Speed Data

Figure 2 provides insights into the historical wind speeds in the state of Michigan, essential for evaluating wind energy potential. It includes average wind speeds at an anemometer height, reflecting variations across different months.

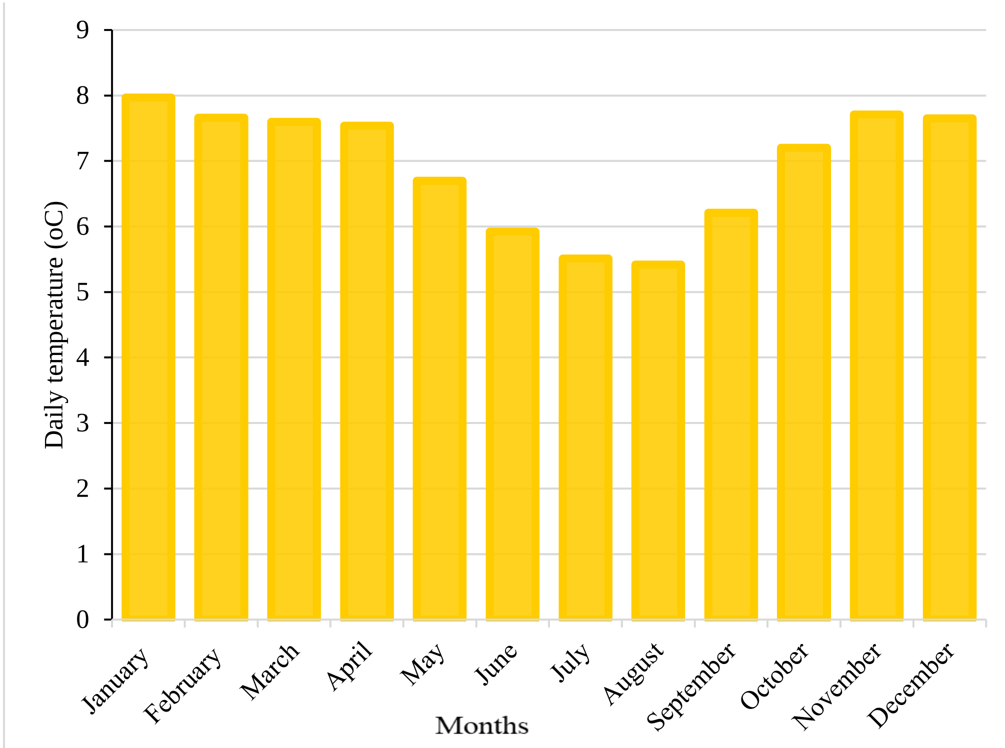


Figure 4.3 Monthly average wind speed data (NASA) [1]

- Load Data

Figure 3 depicts the annual primary AC load in kW supplied by Oakland University (OU), while Figure 4 presents the detailed daily electrical load. This information is vital for designing MG systems that can adequately meet the campus's energy demands.

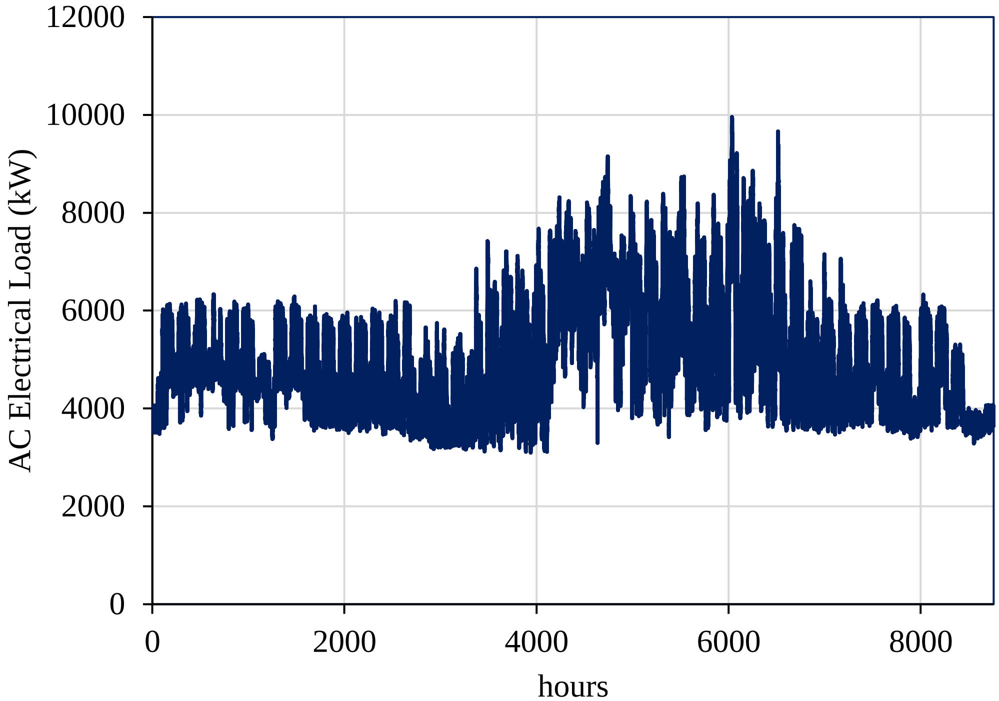


Figure 4.4 Load profile at OU [1]

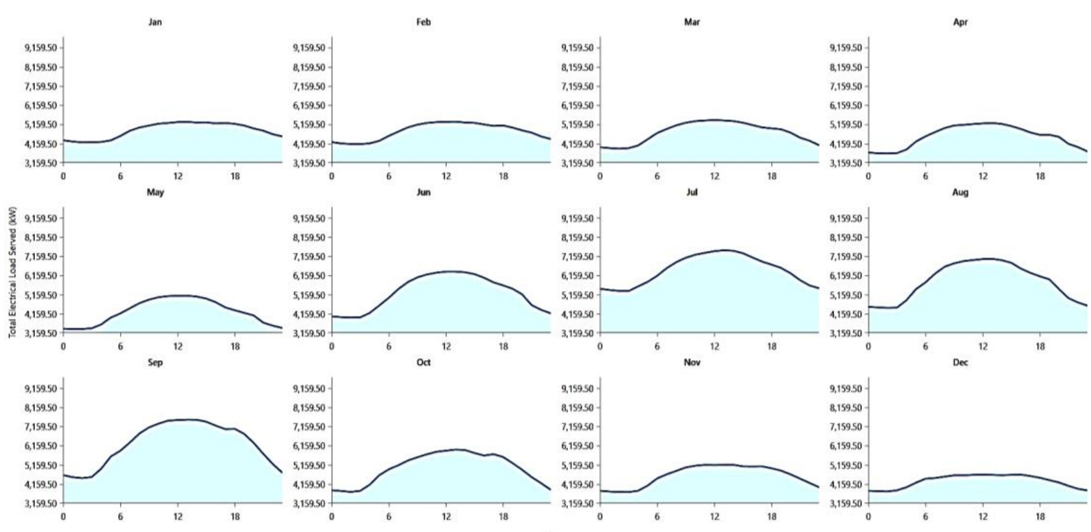


Figure 4.5 Selected electrical load served daily profile (HOMER Pro software) [1]

- Input Project Data into HOMER Pro

  Project-specific data are entered into HOMER Pro, including geographic and climatic data specific to the project site, details of the MG setup including types and capacities of the components, and selection of model parameters that influence simulation outcomes.

- The Selected Microgrid Components

  This step involves the detailed configuration and selection of MG components:

- Potential Locations and System Components

Figure 5 shows potential locations for photovoltaic (PV) panels and wind turbines and outlines the configuration of the MG components campus (CHP , PV , and WT).

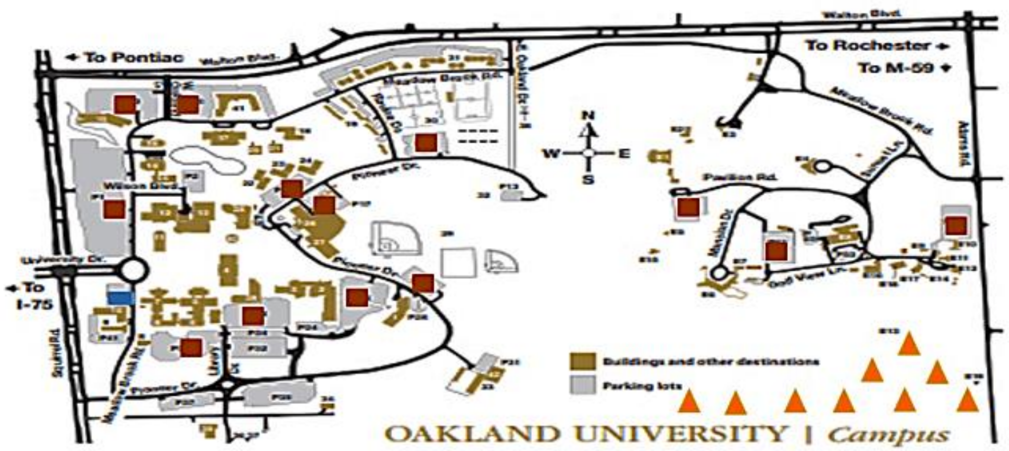


Figure 4.6 Available areas for PV and wind turbines within the university [1]

4.2.3 Deployment Categories

The study categorizes the types of renewable energy systems, including CHP systems, solar PV systems, wind turbines (WTs), and energy storage systems (ESS). Technical and economic indicators, such as capacity, efficiency, cost, and component lifetimes, are crucial for decision-making. Component lifetimes are detailed: solar PV (n=25 years), WT (n=2,260,000 hours), and ESS (n=60,000 hours), summarized in Table 2.

4.2.3.1Cost Parameters

- Net Present Cost (NPC)

  The NPC is calculated as follows:

$$NPC = \sum_{i=1}^{t} i_d (C_{cap} + C_{rep} + C_{O\&M} + C_{fuel} - C_{sellback}) \quad (4.6)$$

where i_d represents discount rate, and C_{cap} C_{rep} $C_{O\&M}$ C_{fuel}, and $C_{sellback}$ represent capital cost, replacement cost, fuel cost, and sellback cost, respectively [34], [45].

The i_d is calculated as:

$$i_d = \frac{1}{(1+i)^n} \quad (4.7)$$

where n represents number of years and i represents

$$i = \frac{i' - f}{i + f}$$

(4.8)

where i′ and f represent, respectively,

The annual cost (C_{ann}) is calculated as:

$$C_{ann} = CRF(i, n) \times NPC \quad (4.9)$$

where $\mathrm{CRF}(\mathrm{i},\mathrm{n})$ is obtained from Equation (19):

$$CRF(i,n) = \frac{i(1+i)^n}{(1+i)^n-1} \quad (4.10)$$

The system is configured in HOMER Pro by inputting each MG component's technical and economic details. The size and capacity, efficiency, cost, and other relevant parameters for the renewable energy sources, energy storage, and other components included in the system design are specified. Then, optimization analysis is employed in HOMER software to determine the optimal system configuration and operation strategy that minimizes the NPC based on the defined system parameters. The present value of NPC is the current value of a future cost or benefit, considering the discount rate and system lifetime. HOMER provides the NPC value directly as part of the optimization analysis results.

- Levelized Cost Of Energy (LCOE)

The LCOE equation calculates the average cost of generating electricity (kWh) over the system's lifetime, considering the initial investment, fuel costs, operational and maintenance expenses, and discounting future costs to their present value [4].

The mathematical equation for calculating the LCOE is as follows:

$$LCOE = \frac{(C_{inv}+C_{fuel}+C_{OM})}{(E_{gen}(1+r)^{(n-1)}} \quad (4.11)$$

where $\mathrm{C_{inv}}$ is the total capital investment cost, including the initial investment in equipment and infrastructure, $\mathrm{C_{fuel}}$ is the total fuel cost incurred over the system's lifetime (n), $\mathrm{C_{OM}}$ is the total operational and maintenance cost over the system's lifetime, and E_{gen} is the total energy generated by the system over its lifetime. (r) is the discount rate, representing the time value of money and the opportunity cost of capital.

Finally, the LCOE equation assumes a constant energy generation throughout the system's lifetime.

$$LCOE = \frac{C_{ann}}{E_{served}} \tag{4.12}$$

CHAPTER FIVE

CONTROLLING

5.1 Control Systems in Microgrids

Microgrids are intended to incorporate the renewable energy resources such as photovoltaic (PV), wind turbines (WT) and combined heat and power (CHP) integrated with battery storage systems (BSS) and take load from the grid as well as the campus. However, an issue associated with renewable energy is that its source is prone to variability and thus poses controls difficulties. These variations due to solar irradiance, wind speed or temperature, etc. make control of the system and controlling the flow of energies not an easy task.

Several control strategies have been proposed, including proportional-integral-derived (PID) controllers, droop control, and fuzzy logic control, all of which have strengths and limitations. As an example, PID controllers are widely used due to their simplicity and effectiveness in regulating stable systems. By adjusting control inputs according to the proportional, integral, and derivative components of the error between a desired and actual system state, these systems work efficiently. In addition, they do not be well suited to systems that are highly variable, such as microgrids using renewable energy sources, as they lack the capability to predict future behavior and optimize control actions over time [136]. As a result, PID controllers are often incapable of handling the complex, multivariable optimization required in dynamic environments where renewable energy output fluctuates rapidly [137].

In the same way, droop control has been widely applied where load sharing among distributed energy resources (DERs) takes place in microgrids. Droop control operates by controlling output of DERs using deviations in the frequency or voltage. Although it is quite easy and efficient to use for maintaining local stability, this method is not very suitable for the controlling of overall system energy networks. For instance, droop control performs relatively worse on islanded microgrids that have high levels of distributed renewable power generation with no support from the main grid. Also, constraints such as battery storage capability and fluctuating renewable energy production are beyond the capabilities of droop control as a microgrid management system [138, 139].

Fuzzy logic controllers have also been incorporated in microgrids for managing uncertain or non-linear appearance of systems with renewable energy resources. By using rules that are obtained in the process of fuzzification, fuzzy logic controllers decide on the control action without having to use an accurate mathematical model of the system in question. It enables them to mitigate on inaccuracies which are likely to be encountered in power generation from renewable resources like variation in solar intensity and wind speed. However, while fuzzy logic controllers also provide flexibility they do not optimize and maybe difficult to tune for optimal energy control in the long term. Further, they cannot be used in situations where the system has more than one control objectives that must be met, such as managing energy storage, interacting with the grid and integrating renewable sources of energy [140].

These differ from the above-mentioned methods in that multi-level control architectures and Adaptive Model Predictive Control (AMPC) have proven to be more efficient solutions to the complexities of microgrids. Multi-level control which partitions the control system into primary control, secondary control, and tertiary control are more flexible and coordinated with the DERs, storage systems, and interacting grid [141]. The primary level is mainly related to real time stability, the secondary level concerns the power flow control for distribution generation resources and the tertiary level deals with the micro-grid and the utility. Such a structure enables local control and system-wide coordination, which makes hierarchical control very appropriate for systems with high RE penetration [142].

Additionally, because of Adaptive MPC, there is a highly effective method of optimizing microgrids. Compared with normal controllers, the Adaptive MPC controller predicts the behavior of the system in the future and adapts the current control actions with the variation of time horizon. This capability is significant in microgrids where residents rely on renewable energy and where load demands vary frequently. Due to the recursive updating of the predictions and control horizons in Adaptive MPC, the energy is efficiently managed, the connectivity with the utility grid is diminished, and the system stability is optimized, even in ambiguity [143].

In this research, adaptive MPC integrated with a multi-level control system is employed to manage the operation of a microgrid. Using live meteorological data, the system can provide accurate transmission of data, allowing real-time control actions to be adjusted dynamically. The integration of Adaptive MPC also enhances the microgrid's capability to be powered by renewable energy sources, reduces dependence on grid support, and improves the management of system stability.

5.2 Adaptive Model Predictive Control (MPC)

Adaptive Model Predictive Control (MPC) is a dynamical control method that actively computes control actions based on predictions of future system's condition concerning to the model prediction. Adaptive MPC, on the other hand, does not require controlling inputs for current system conditions like other conventional controlling systems, but it utilizes a model of the future behaviors in the system and the resultant energy flows. This is more so the case in microgrids where PV and WT – renewable energy sources exhibit high variability and intermittency. Compared with the conventional MPC, the adaptive MPC augments the preview horizon that dynamically alters to ensure the controller adaptability in responding to fluctuations in either renewable power supply or load consumption [144].

Nevertheless, microgrids have certain limitations attributable to the randomness of green power suppliers. These challenges are overcome in Adaptive MPC as it periodically recalculation its predictions as well as the corresponding control actions based upon real-time data of the microgrid. This is effective in the management of energy; reduces reliance on the utility grid and it also sustains stability of the system even when there is intermittent in the generation of renewable energy [145].

5.3 Principles and Design of Adaptive MPC

Adaptive MPC used in microgrid control entails adoption of a state-space model where the future states of the system are predicted. In contrast to the conventional control schemes, Adaptive MPC not only uses current states of the system but also predicts the future states and alters the control signals accordingly to have desired system performance. The update prediction horizon equation of the adaptive MPC can be expressed as:

$$H_{new} = max\ (H_{min}, min(H_{max}, H_{current} + f_{adj} \cdot (P_{renwable}^{pred} - P_{load}^{pred}))) \qquad (5.1)$$

Where: H_{new}: The updated prediction horizon, H_{min}, H_{max}: Minimum and maximum allowed prediction horizons, $P_{renwable}^{pred}$: Predicted renewable power generation, P_{load}^{pred}: Predicted renewable power generation, f_{adj}: Adjustment factor for the horizon length.

AMPC is illustrated in Figure 5.1, which displays the prediction horizon, where future outputs are predicted as a function of current and past control inputs (blue and yellow lines). Obtaining optimal energy balance and efficiency requires the creation of reference trajectories (red lines), which represent the desired path of the system. The predicted output (purple line) is generated by Adaptive MPC's calculation and adjustment process, which occurs in real-time because of actual system performance, based on the measured output (orange line). As illustrated in the accompanying visual representation, Adaptive MPC is an important tool for managing the complexities of renewable energy in microgrids.

- The control architecture of the system employs adaptive MPC to manage power flows and battery charging/discharging decisions based on real-time forecasts of load and generation. MPC dynamically optimizes the SoC of the battery and ensures that energy is efficiently distributed across the system [3]. The SoC dynamics are governed by the following equation.

  The SoC dynamics of the battery in real-time are governed by the following equation:

$$SoC(k+1) = SoC(k) + \frac{\eta_{charge} \cdot P_{charge}(k) \cdot \Delta\, t - P_{discharge}}{C_{battery}} \tag{5.2}$$

Where: η_{charge}: is the charging efficiency,$P_{charge}(k)$: is the charging power at time (k), $P_{discharge}$: is the discharging power at time (k), $C_{battery}$: is the battery capacity, $\Delta\, t$: is the time step.

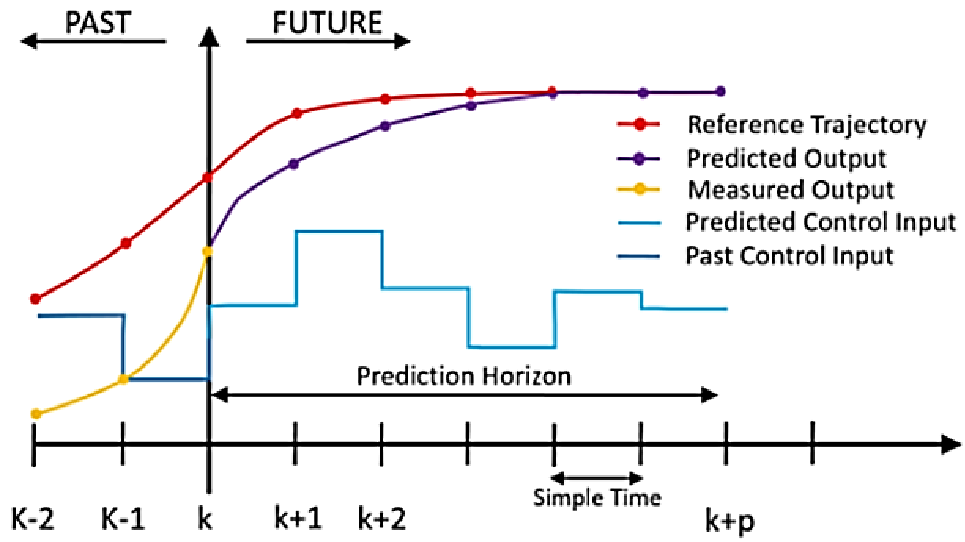


Figure 5.1 Model Predictive Control Operation [146]

- Excess Power:

  the excess power from renewable energy generation will be used to charge the battery, the equation for this can be expressed as:

$$U(k) = f(SoC(k), P_{excess}\,(k)) \tag{5.3}$$

Where: $SoC(k)$: The battery's state of charge at time (k), $P_{excess}\,(k)$: The excess power from PV and WT at time(k), defined as:

$$P_{excess}\,(k) = (P_{PV}\,(k) + P_{WT}\,(k)) - Load(k) \tag{5.4}$$

- If $P_{excess}\,(k) > 0$, the excess power is available for battery charging.
- If $P_{excess}\,(k) < 0$, there is no excess power, and the battery will not charge.

The input control $U(k)$ is the real-time decision on whether to charge the battery or not, based on the available excess power and the SoC of the battery.

- Charging Condition:

  The battery will only charge if excess power is available, and this can be expressed as:

$$\begin{cases} P_{excess}(k), & If\ P_{excess}\ (k) > 0\ and\ SoC\ (k) < SoC_{max} \\ 0, & If\ P_{excess}\ (k) \leq 0\ or\ SoC\ (k) \geq SoC_{max} \end{cases} \tag{5.5}$$

5.4 Multi-Level Control Architecture with Adaptive MPC

In the present study, a multi-level control system is implemented to manage the microgrid, with Adaptive Model Predictive Control (AMPC) utilized across all three control levels. Each level has distinct responsibilities that contribute to maintaining the efficiency and stability of the microgrid for effective energy management.

- Primary Control Level

  The primary control manages local operations, such as individual distributed energy resources (DERs) and battery state of charge (SoC), ensuring that local generation and load balance are maintained. This allows for real-time monitoring and coordination of actions across the system, enhancing the overall efficiency and stability of the microgrid.

- Secondary Control Level

  At this level, the Adaptive MPC coordinates the operations of multiple distributed energy resources (DERs) and storage systems, adjusting power flows to optimize energy use. The controller dynamically adjusts the state of charge (SoC) and power generation based on current load demand and renewable energy production forecasts.

- Tertiary Control Level

  The tertiary control oversees the entire microgrid and integrates long-term system-wide objectives, such as minimizing grid dependence and optimizing renewable energy use. Adaptive MPC at this level ensures that real-time data is used to adjust power dispatch, prioritizing renewable energy and ensuring efficient utilization of battery storage.

The system ensures the passage of real-time data from the primary and secondary levels to the Adaptive MPC controller, allowing it to adapt to fluctuating generation, load, and storage scenarios. Figure 5.1 illustrates Microgrid Multi-levels Control Flowchart.

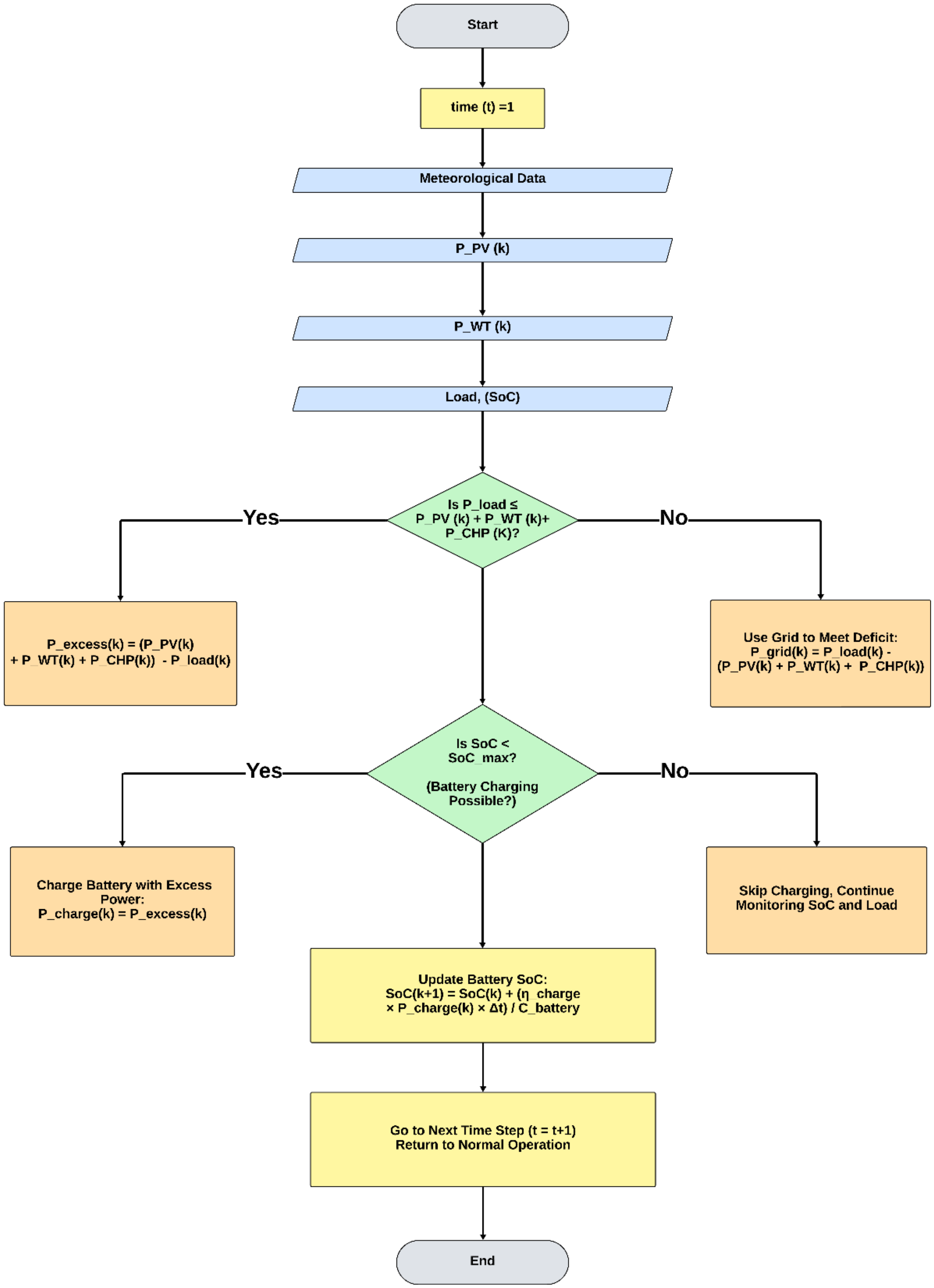


Figure 5.2. Microgrid Multi-levels Control Flowchart

5.4.1 Proposed configuration

The microgrid, as shown in Figure 5.3, comprises a utility grid, solar energy, wind turbines, combined heat and power (CHP), and battery storage systems. The entire system will be modeled mathematically in MATLAB 2024a to enable faster simulations.

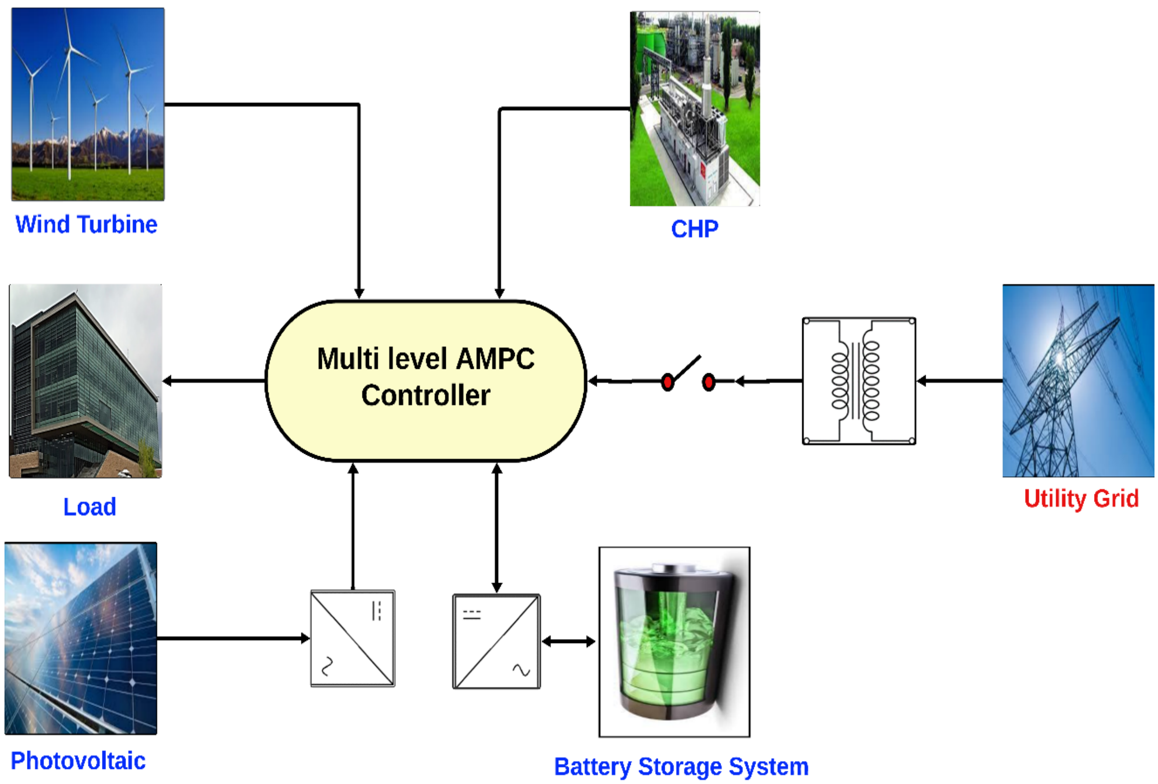


Figure 5.3. Proposed Microgrid Configuration

The microgrid system design for Oakland University focuses on reducing dependency on the utility grid by utilizing a Combined Heat and Power (CHP) unit, currently supplying 4369 kW to meet almost half of the daily energy demand. Simulations of photovoltaic (PV) panels and wind turbines are included to assess their potential contributions to the energy mix. The battery storage system is intended to store excess energy from the simulated PV and WT systems for use during low generation periods, with any remaining deficit supplied by the utility grid.

CHAPTER SIX

SIMULATIONS AND RESULTS

6.1 Key Findings from the Comprehensive Review of University Campus Microgrids

The review of existing and emerging microgrids at university campuses around the world reveals several significant insights. These microgrids serve as models for integrating renewable energy sources, improving energy efficiency, and enhancing resilience in the face of grid disruptions. The key findings outlined below demonstrate how universities have optimized their energy systems, achieved economic and environmental benefits, and contributed to sustainable energy research and development.

6.1.1 Geographical and Climatic Adaptation

Universities have tailored their microgrid energy mixes based on local conditions. For example, the University of California, San Diego, produces 85% of its electricity and 95% of its heating and cooling needs through a hybrid system involving solar, gas, and steam turbines, customized to its climate and geographical location.

6.1.2. Hybrid Energy Systems

Hybrid microgrid configurations have proven effective in optimizing energy use. Oakland University, for instance, integrates geothermal, photovoltaic (PV), solar thermal, and combined heat and power (CHP) systems into its microgrid to achieve a balanced and efficient energy mix.

6.1.3. Economic Efficiency

Microgrids have demonstrated their ability to reduce operational costs significantly. The Illinois Institute of Technology, through the optimization of its energy management systems, achieved a 9% reduction in annual operational costs, from USD 140,497 to USD 126,644.

6.1.4. Energy Independence and Resilience

University microgrids have greatly enhanced resilience during grid outages. For example, Princeton University's microgrid, which includes gas turbines and solar fields, maintained uninterrupted power during Hurricane Sandy, while much of the region faced prolonged blackouts.

6.1.5. Environmental Impact

The adoption of microgrids has also led to substantial reductions in environmental impacts. The University of California, San Diego, reports 75% fewer emissions compared to traditional systems, showcasing the potential of campus microgrids to contribute to climate change mitigation.

6.1.6 Comparison of Microgrid Configurations in University Campuses

Many institutions of higher education in many parts of the world have constructed microgrids onsite using different layouts to address their energy shortages. These infrastructures are classified under three major schematics as shown schematically in Figure 22, namely, A self-sufficient configuration with sine wave alternating current Configuration A Hybrid PV grid AC coupled layout, Configuration B Hybrid PV WT grid AC coupled layout and Configuration C Hybrid PV diesel generator grid AC coupled layout. The gap analysis aided in understanding the demand on the designs of configurations across campuses showed that configuration A is dominant with verification of A having ridged more installations than the rest due to adoption. This is as a result of its effectiveness as the simplest and most inexpensive. Configuration A is simple as it does not have any energy storage component and operates as a hybrid pv grid which is low cost and low maintenance particularly for colleges in search of green energy alternatives.

On the other hand, Configuration C, which is the hybrid PV-diesel generator system configuration, is the least achieved configuration. This is because of the expensive price of fossil fuel which contributes to air pollution, a factor that modern institutions of higher learning are looking to eradicate. Configuration B and Configuration D are not very often in use, however, any of them could be considered as an option depending on the energy profile and potential of the region. Configuration B presents the option of deploying turbines for windswept areas, whereas Configuration D utilizes combines heat and power generator which efficiently utilizes energy through the simultaneous generation of heat and electricity, however its application is restricted by the cost and intricacies involved. Figure 6.1. illustrates Distribution of Campus Microgrid Configurations

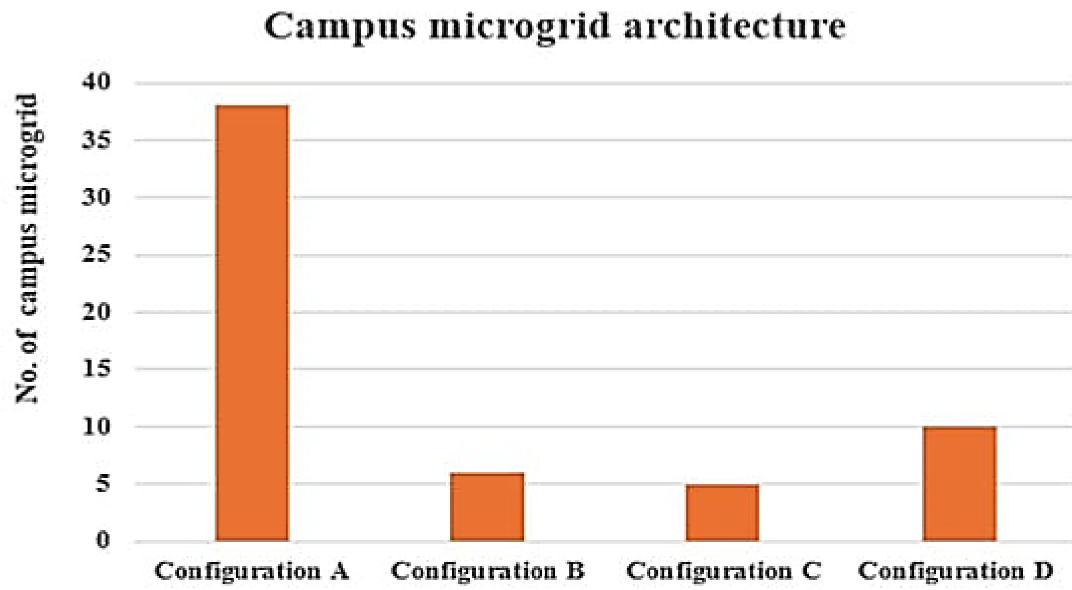


Figure 6.1. Distribution of Campus Microgrid Configurations

Furthermore, Configuration A is the most prevalent in the campus microgrid context as it is cheaper and easier to implement than the others, however, configurations C and more can be hardly implemented due to higher expenses and pollution-related issues. This paper is aimed at a consolidated analysis of microgrid systems utilized on university campuses from the perspective of its various principles, configurations and applications, complemented by a comparative study of renewable energy resources – geothermal energy (GE), wind energy (WT) and solar energy (PVs). Cost, accessibility, effectiveness, and negative influences on the environment were among the aspects evaluated in order to determine the best microgrid configurations for university energy requirements.

6.2 Optimal Microgrid Design Using HOMER Software

6.2.1. System Configurations Simulation Results

- System 1: Grid and CHP

The proposed system combines a grid and CHP, as shown in Figure 6.2. Figure 6.3 provides the output power from the main grid and the CHP system.

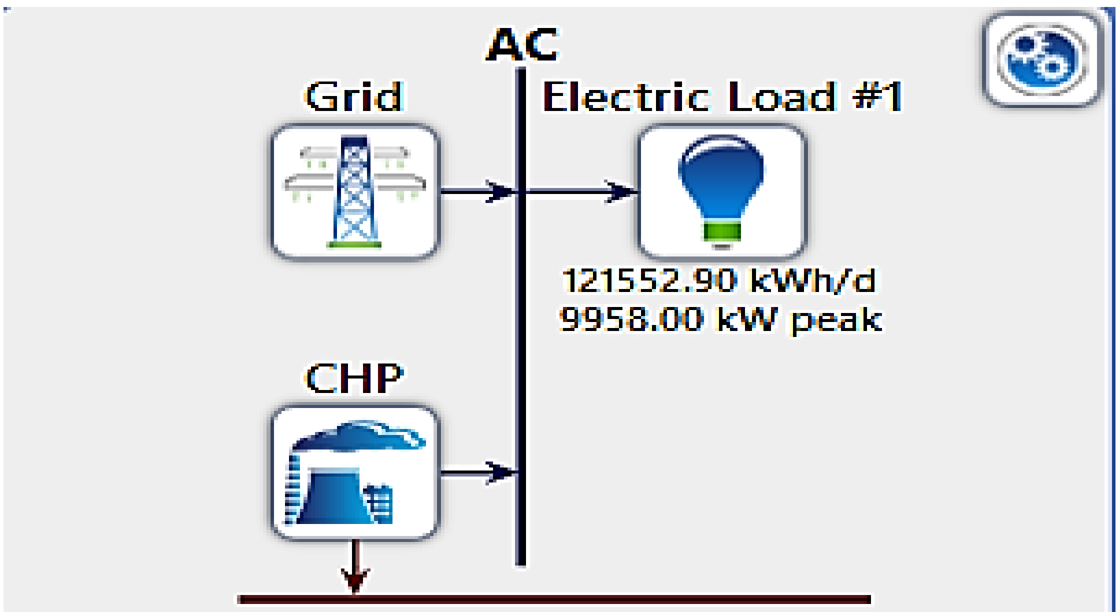


Figure 6.2 System 6.1: grid and CHP design [1]

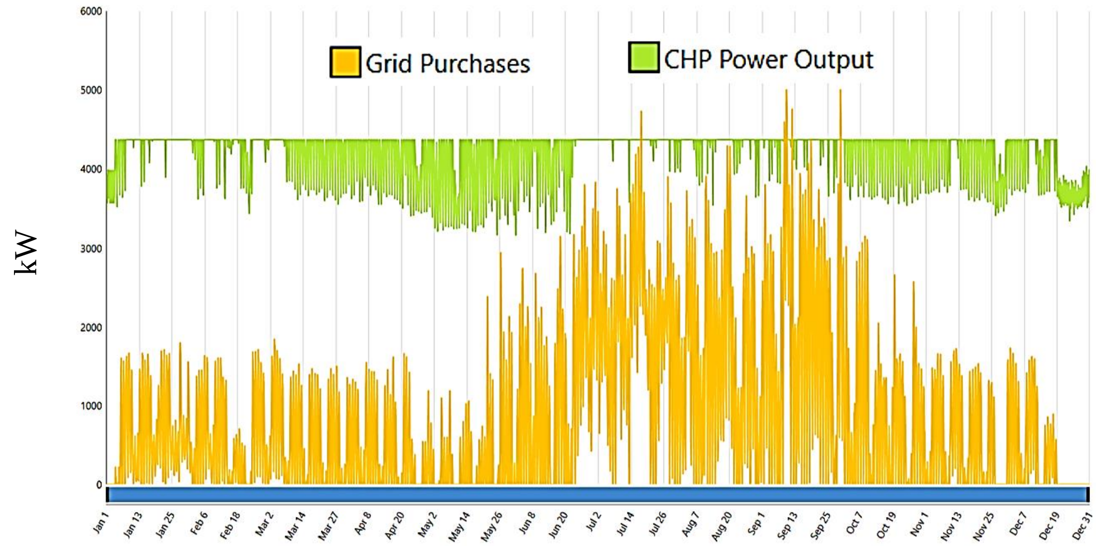


Figure 6.3 Output power (System 1: grid and CHP) [1]

- System 2: Grid, CHP, PV

System 2 combines a CHP system, grid connection, and solar PV resources to meet the energy demand, as shown in Figure 6.4. The system can track the following: (a) energy purchased from grid, (b) energy sold to grid, (c) CHP output power, and (d) PV power output. More, specifically, this proposed system involves purchasing energy from the grid when the CHP and PV systems are unable to meet the load demand, selling excess energy back to the grid when the CHP and PV systems generate more power than required, utilizing the electrical power generated by the CHP system, and harnessing the electrical power generated by the PV system, as illustrated in Figure 6.4 and Figure 6.5, respectively.

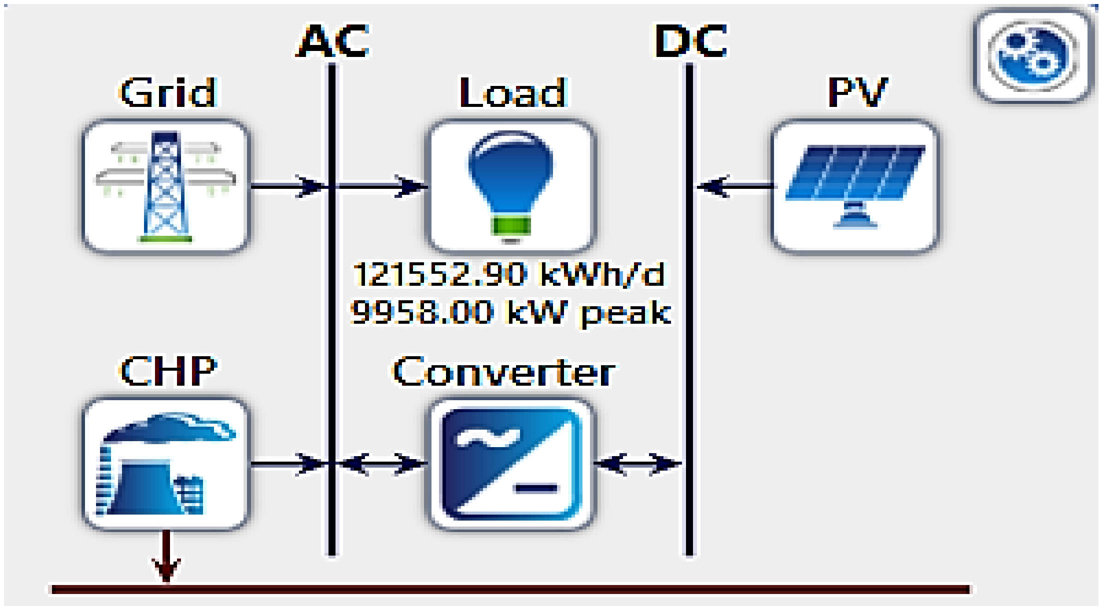


Figure 6.4. System 2: grid, CHP, and PV design [1]

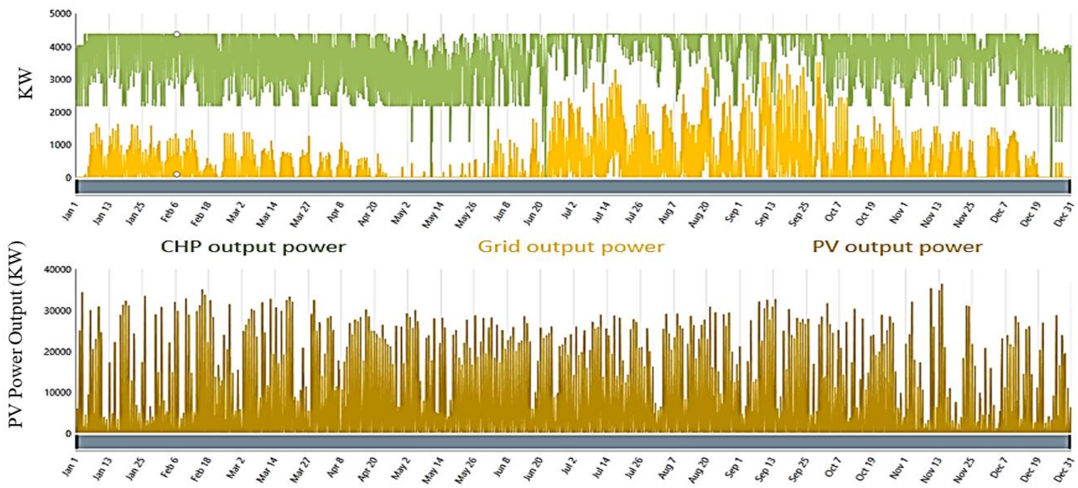


Figure 6.5. Output power (System 2: grid, CHP, and PV) [1]

- System 3: Grid, CHP, PV, ESS

This system integrates multiple energy resources, including the grid, a CHP system, solar PV panels, and an ESS, as shown in Figure 6.6. This combination allows for a more robust and flexible power generation and management approach. Figure 6.7

shows the output power from each resource to meet the overall energy demand. The ESS state of charge provides valuable information for managing energy supply and demand.

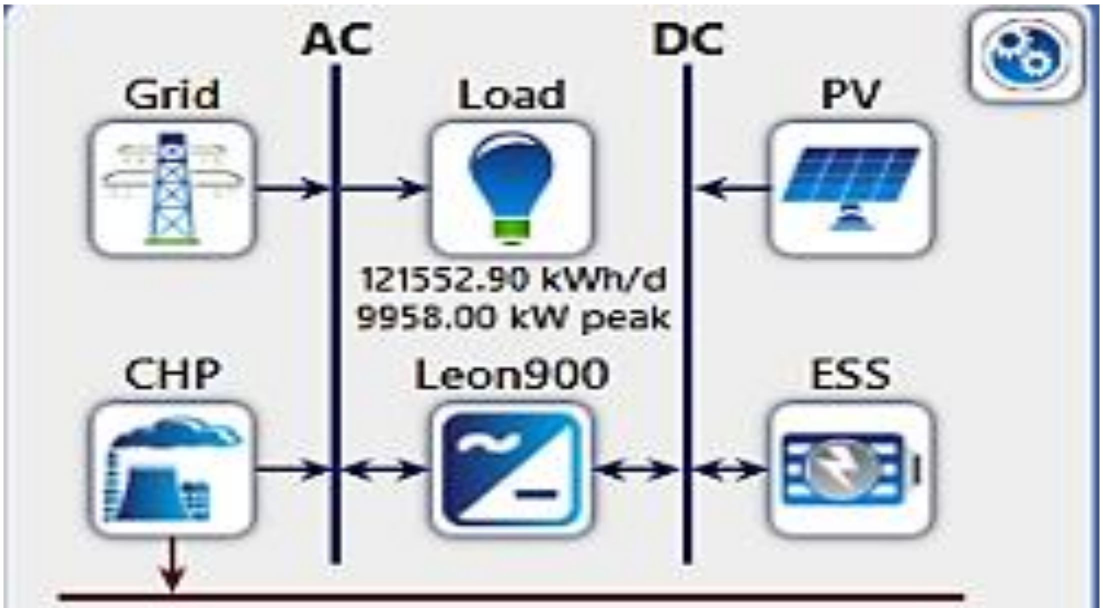


Figure 6.6. System 3: grid, CHP PV, and ESS design [1]

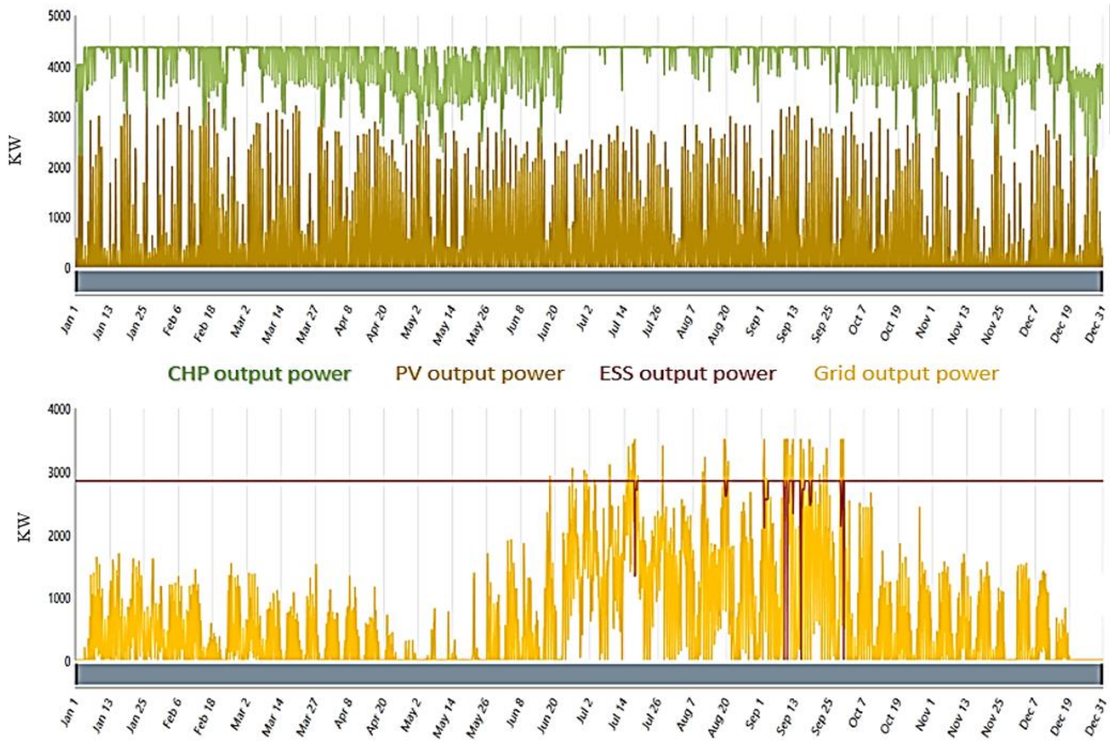


Figure 6.7. Output power (System 3: grid, CHP, PV, and ESS)

- System Grid, CHP, and WT

The WT is integrated with a grid and a CHP system in this system, as shown in Figure 6.8. Figure 6.9 shows the output power from the grid, a CHP, and a WT.

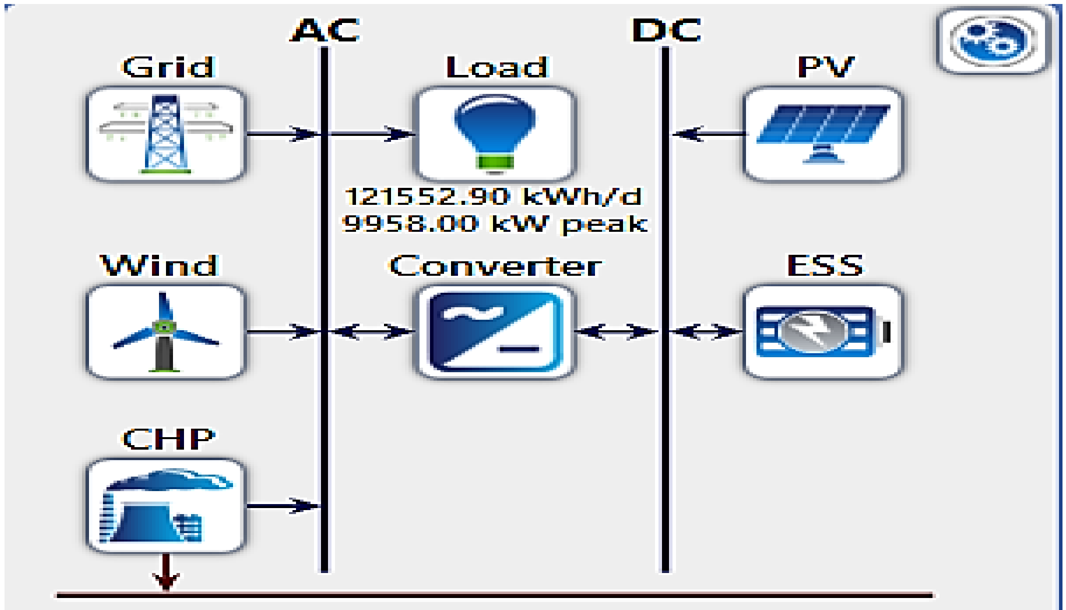


Figure 6.8. System 5: grid, CHP, wind, PV, and ESS design

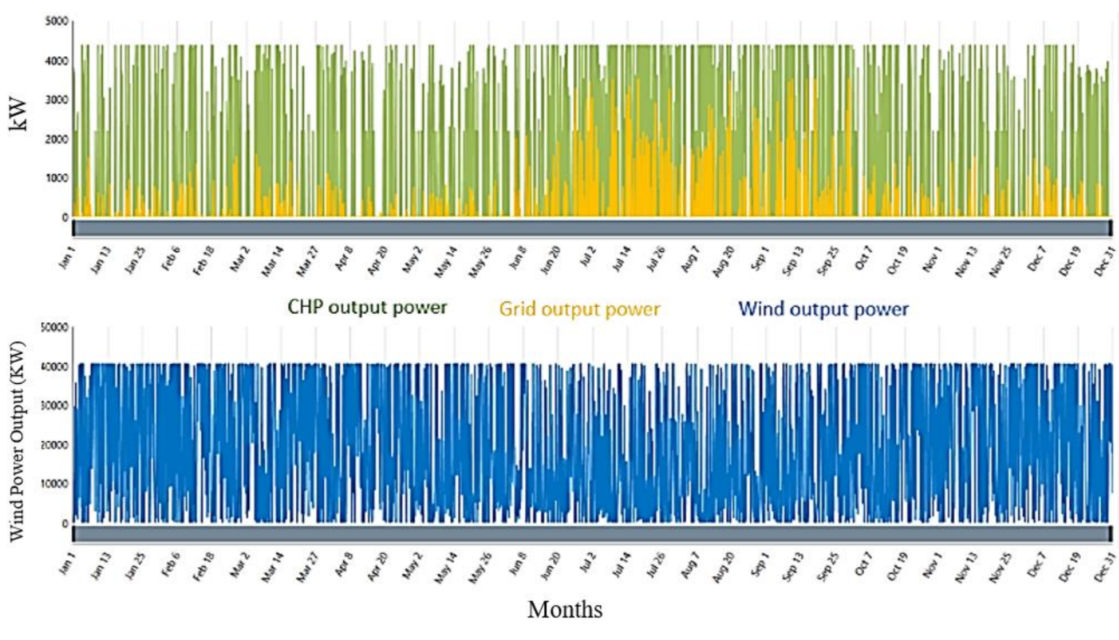


Figure 6.9. Output power (System 4: grid, CHP, and wind) [1]

- System 5: Grid, CHP, PV, WT and BSS

The output power from each source in System 5 varied according to the renewable energy resources harnessed, as shown in Figure 6.10. Figure 6.11 depicts the output power from each source in the system and provides the contribution of each energy source to the overall power generation. Upon analysis, it is obvious that the WT generates the highest amount of power annually compared to other sources. WT indicates that it has a dominant role in power generation. This observation highlights the ample availability of wind resources in the system's location and the efficiency of the WT in harnessing this renewable energy source. On the other hand, the power output from other sources, such as solar PV, the grid, ESS, and CHP is relatively lower. The grid serves as a backup power source when PV generation is insufficient. In addition, the ESS is incorporated to store excess PV energy and supply electricity during periods of low or no generation.

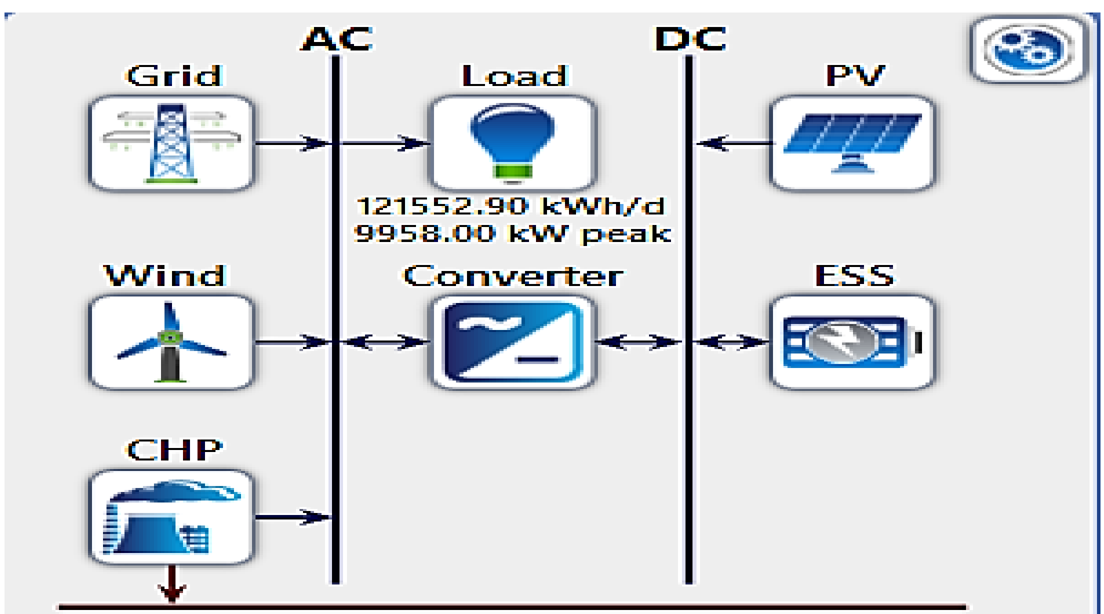


Figure 6.10. System 5: grid, CHP, wind, PV, and ESS design [1]

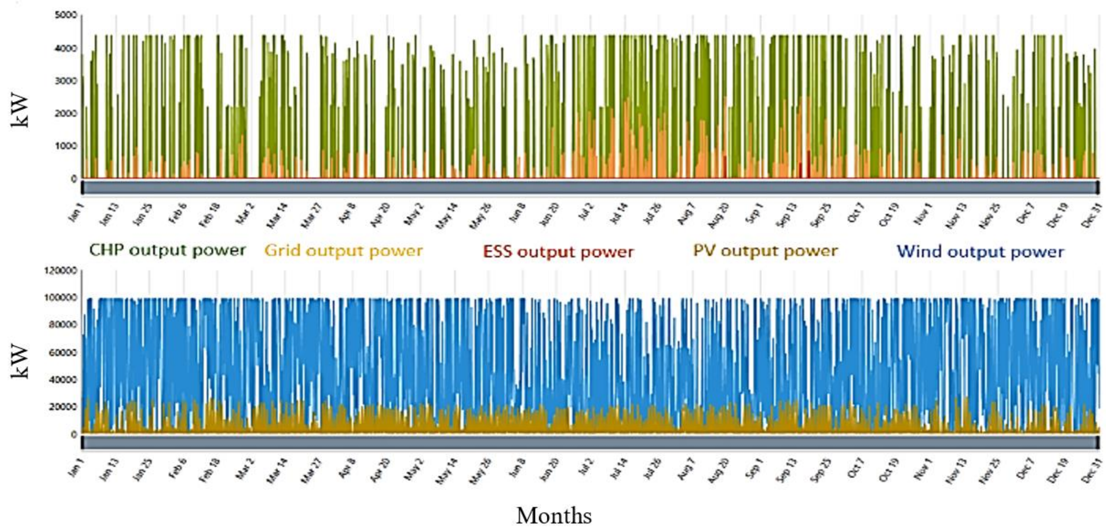


Figure 6.11. Output power (System 5: grid, CHP, PV, ESS, and wind) [1]

- System 6: CHP, Wind, PV, and ESS (Islanded Grid)

In this system, an islanded grid is proposed. Figure 6.12 illustrates the system components. It includes the CHP, wind, PV, and ESS. The output power from each resource provides a visual representation of the contributions made by different sources in meeting the load power demand. Figure 6.13 shows that the WT resource covers much of the load power. The other resources, although less prominent, still play a role in meeting the load power demand. Their contributions may be comparatively less but are nonetheless valuable in ensuring a reliable and balanced power supply.

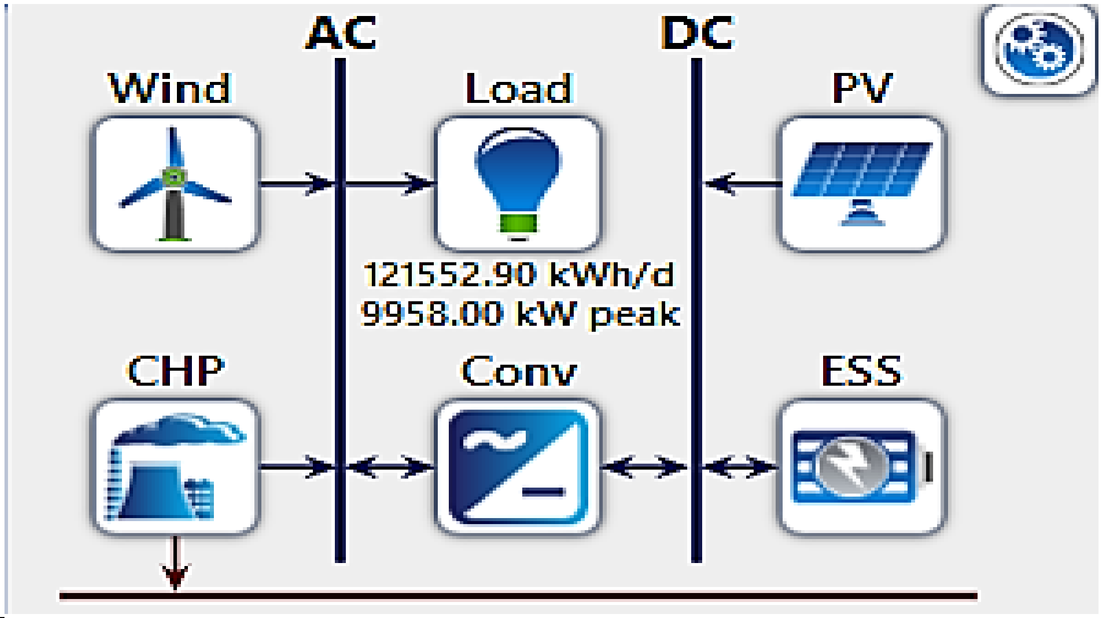


Figure 6.12. System 6: CHP, WT, PV, and ESS design [1]

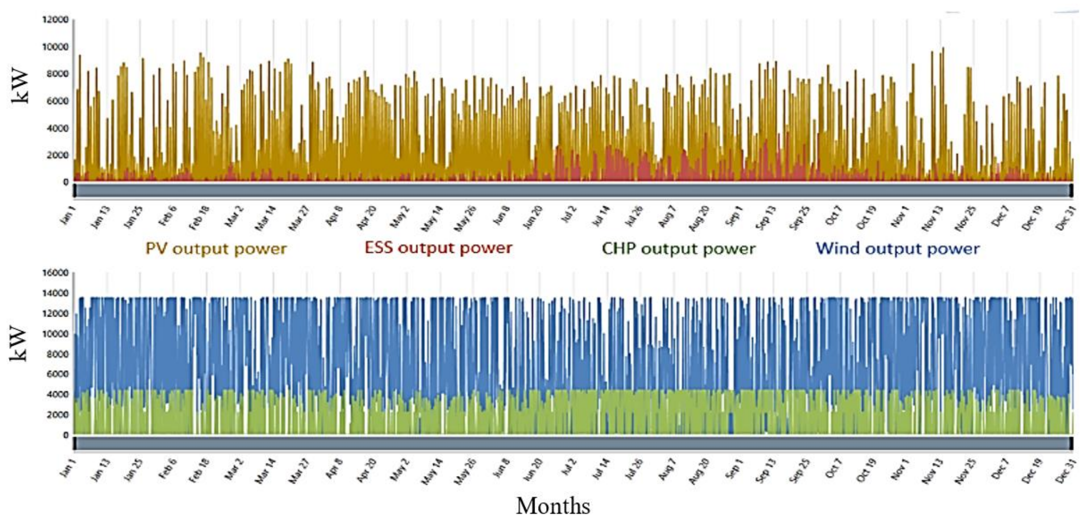


Figure 6.13. Output power (System 6: CHP, PV, ESS, and WT) [1]

6.2.2. Determination of Oakland University System

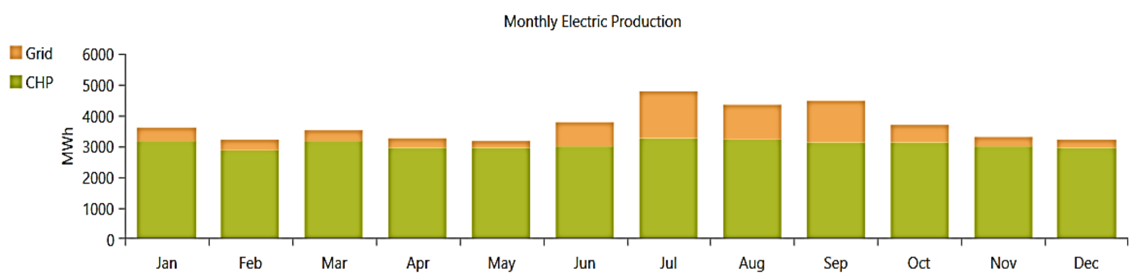
Whether integrated or islanded for the OU campus, the design of an MG requires consideration of renewable resource availability, load demand profiles, system reliability, and cost-effectiveness. The specific combination of energy sources and storage systems should be selected based on the university's energy requirements, renewable resource potential, and sustainability goals. More specifically, the available rated CHP station at OU covers less than 50% of the peak load (10 MW), which indicates that the CHP station needs to meet a significant portion of the electrical demand. This is due to the limitations in the capacity of the CHP and variations in load demand throughout the months. Moreover, the monthly electric generation from the CHP station would vary depending on the system's operational hours, efficiency, and maintenance schedule. However, in this work, the simulation maintains the output power constant. Recently, the grid covered the other portion of the demand load, which is more than 50% when the load exceeds the peak value.

Table 6.1 summarizes the HOMER Pro results for all proposed system [1] configurations, and Figure 6.14 (a to g) illustrates the determination of the renewable output power penetration in meeting the OU electricity requirements. Since the monthly power generated from the PV could be influenced by solar irradiation, seasonal variations in solar availability and weather conditions can impact the PV production levels throughout the year. However, it suggests emphasizing renewable energy integration, reducing greenhouse gas emissions, and achieving sustainability goals. The monthly electric production from each source must be carefully managed and optimized to ensure that the total load demand is met consistently. It requires accurate forecasting of the load demand and balancing the generation from different sources. This could involve load scheduling and energy storage utilization to manage the variations in supply and demand. Certain months may exhibit higher electric production, while others may show lower output.

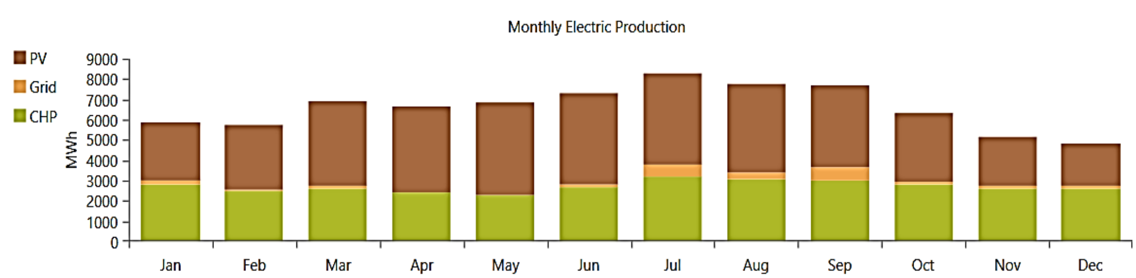
This variation can be attributed to the fact that solar PV production might peak during the summer months in Michigan when sunlight is abundant, while wind power generation could be higher in the vicinity of the OU campus during winter months. This research provides an opportunity to assess the system's overall performance in meeting the electricity demand for OU throughout the year. By examining the monthly trends, we can identify any periods of surplus in electric production. This information can guide system sizing, resource allocation, and optimization decisions to ensure a reliable and efficient electricity supply. Furthermore, it can help identify areas for improvement or potential challenges. For example, if there are significant variations or dips in electric production during certain months, additional system components or adjustments to system parameters are needed. It is important to note that the paper represents a specific scenario based on assumptions and modeling inputs. The actual power generation may vary depending on various factors, particularly the system design and resource availability. In the future, proper MG design and energy management will ensure consistent and reliable electric power throughout the year by utilizing optimization algorithms.

Table 6.1 Summaries of the results for system configurations

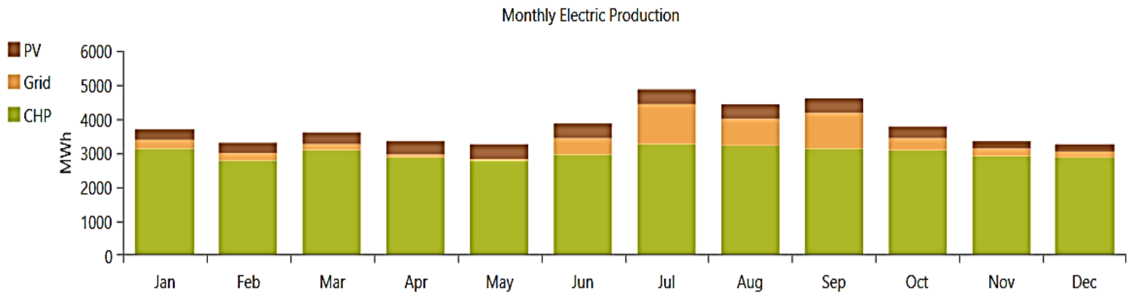
System	GRID (kW)	PV (kW)	WT (kW)	CHP (kW)	ESS: Count, 1 MW	Converter (kW)	NPC USD	LOCE (USD/kWh)
System 1	5000	-	-	4369	-	-	45.6 M	0.0795
System 2	3500	32,288	-	4369	-	2567	94.1 M	0.163
System 3	3500	3146	-	4369	1	14,938	52.2 M	0.0911
System 4	3500	-	40,500	4369	-	-	9.6 M	0.000393
System 5	2500	12,155	30,000	4369	15	1494	30 M	0.0274
System 6	-	10,930	12,000	4369	32	4907	88 M	0.175



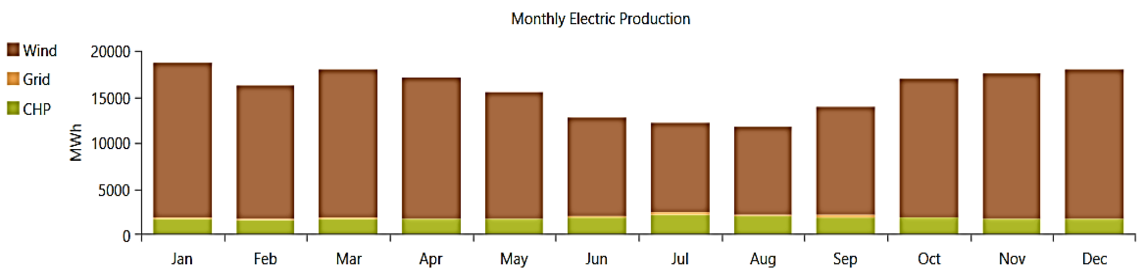
(**a**) System 1



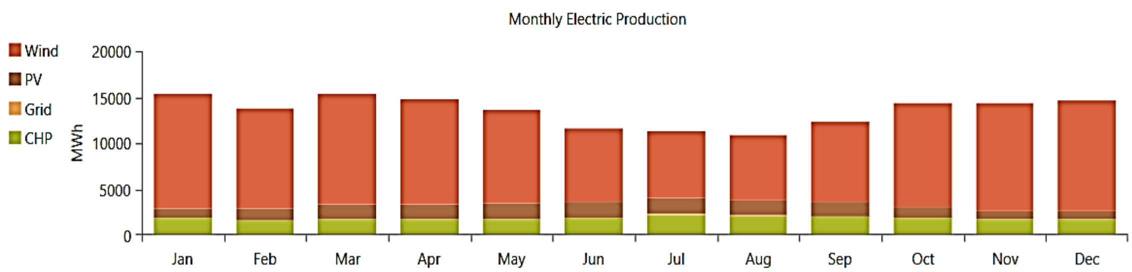
(**b**) System 2



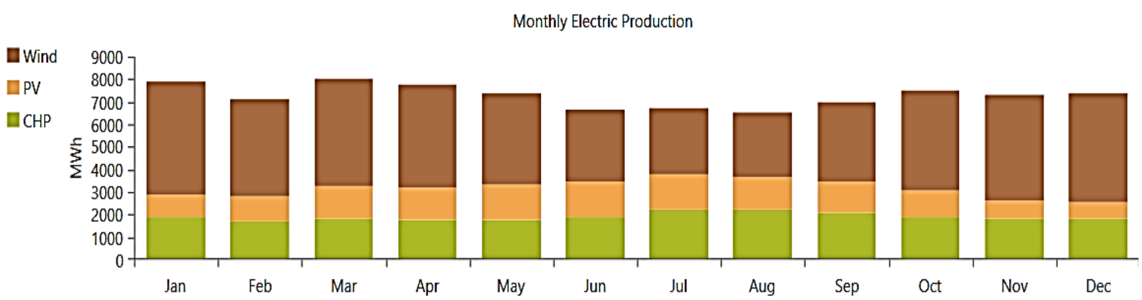
(**c**) System 3



(**e**) System 4



(**f**) System 5



(**g**) System 6

Figure 6.14. Monthly electric production for all proposed systems [1]

6.2.2 Simulation results discussion for each configuration

- System 1: The maximum CHP output power of 4,369 kW represents the highest electrical power generated by the CHP system integrated into the MG. The system draws a maximum capacity of 5,000 kW from the grid, suggesting the highest load requirement that the MG's generation sources cannot meet. In addition, the NPC is USD 45.6 M, with an LCOE of 0.0795 USD/kWh. These values demonstrate a relatively moderate NPC and LCOE.
- System 2: The solar PV resource contributes a maximum output power of 32,288 kW. The grid connection provides a maximum output power of 3,500 kW. The converter provides a maximum output power of 2,567 kW. In addition, the NPC is USD 94.1 M, and the LCOE is 0.163 USD/kWh. The higher NPC and LCOE values in System 2 can be attributed to the addition of PV, which incurs higher upfront costs than in System 1. However, the LCOE is still within an acceptable range, indicating a competitive cost per unit of electricity generated.
- System 3: PV (3,146 kW), CHP (4,369 kW), ESS (1 MW), and the grid (3,500 kW). The simulation results for the proposed system reveal an NPC of USD 52.2 M and an LCOE of USD 0.0911/kWh. Including an ESS in System 3 contributes to the higher NPC than in System 1. However, the LCOE remains relatively competitive, suggesting efficient utilization of energy resources and storage.
- System 4: The wind power resource provides a substantial output of 40.5 MW, the system's capacity to harness renewable energy from the wind. The CHP system contributes a maximum power output of 4.369 MW. The grid connection supplies a maximum power output of 3,500 kW, acting as a backup power source

and ensuring a reliable electricity supply. The NPC of USD 59.4 M has an LCOE of USD 0.028/kWh. The low NPC and LCOE values signify the economic viability and cost-effectiveness of the system.

- System 5: The solar PV system generates an output power of 12.155 MW. The wind power resource substantially contributes, providing an impressive output power of 30 MW. The utility grid is a backup power source with an output power of 2,500 kW. With a capacity of 15 MW, the ESS provides flexibility in managing power demand and supply fluctuations. The CHP system contributes a maximum power output of 4,369 kW. The converter, rated at 1,494 kW, enables efficient power flow management within the system. It demonstrates an NPC of USD 30 M and an LCOE of 0.0274 USD/kWh. Including multiple energy sources and storage systems contributes to a higher NPC than System 4. However, the LCOE remains significantly low, indicating an economically viable and efficient system. This relatively low NPC tells a financially feasible and cost-effective system design. Integrating multiple renewable energy sources, along with the efficient operation of the CHP system and utilization of the ESS, contributes to the lower NPC. Furthermore, the simulation results emphasize the importance of accurate resource assessment and optimal sizing of the system components. The substantial output powers from wind and solar PV demonstrate the potential for harnessing significant amounts of renewable energy. Utilizing an energy storage system and the efficient operation of the CHP system contribute to load balancing and improved system performance.

- System 6: This system exhibits an NPC of USD 88 M and an LCOE of 0.175 USD/kWh. The higher NPC and LCOE in System 6 can be attributed to including multiple energy sources and storage systems, which incur higher upfront costs. However, the LCOE remains competitive, considering the enhanced reliability and resilience of the system.

Each of the monthly electric production (MEP) values for all proposed system configurations utilizes various sources to meet the electricity demand, as follows: In System 1, the primary source of electricity is the combined heat and power (CHP) system, which covers 43% of the total load. If the electrical demand exceeds the capacity of the CHP, the additional power required is obtained from the grid. System 2 adopts a diversified approach, with PV solar panels contributing 22% of the total load demand. The CHP system covers 43% of the load, while the remaining portion is procured from the grid. In System 3, energy production is diversified using multiple sources. PV solar panels contribute 9% of the load, and the CHP system covers 43%. Around 35% of the load demand is sourced from the grid, with the remaining portion fulfilled by a battery system. In System 4, a WT generates 35% of the load, with the CHP system covering 43%. In System 5, the CHP system supplies 43% of the load, the grid provides 25%, and a combination of WT, PV, and ESS delivers the remaining portion. In System 6, the energy production is diversified using WT, contributing 40% of the total load demand. The battery and PV systems combine to make up the remaining 35%.

These different system configurations demonstrate the integration of various energy sources to meet the load demand. By diversifying the energy mix, these systems enhance reliability, optimize resource utilization, and reduce dependency on the grid. The specific combination of energy sources in each system configuration allows for flexibility and potential cost savings while considering the unique characteristics of each source in terms of generation capacity and availability.

Figure 6.15 presents the annual renewable energy production for all proposed systems (System 1 to System 6). Each system exhibits different capacities for grid connection, PV solar, WT, CHP, and ESS. System 1 solely relies on a grid connection with no integration of PV, WT, or ESS. On the other hand, Systems 2, 5, and 6 demonstrate the significance of renewable sources with varying capacities of PV solar and WT. System 6 stands out as an off-grid system with no grid connection but a substantial WT capacity. The diverse energy source capacities highlight the importance of careful planning and optimization to ensure cost-effectiveness, sustainability, and resilience in microgrid operations.

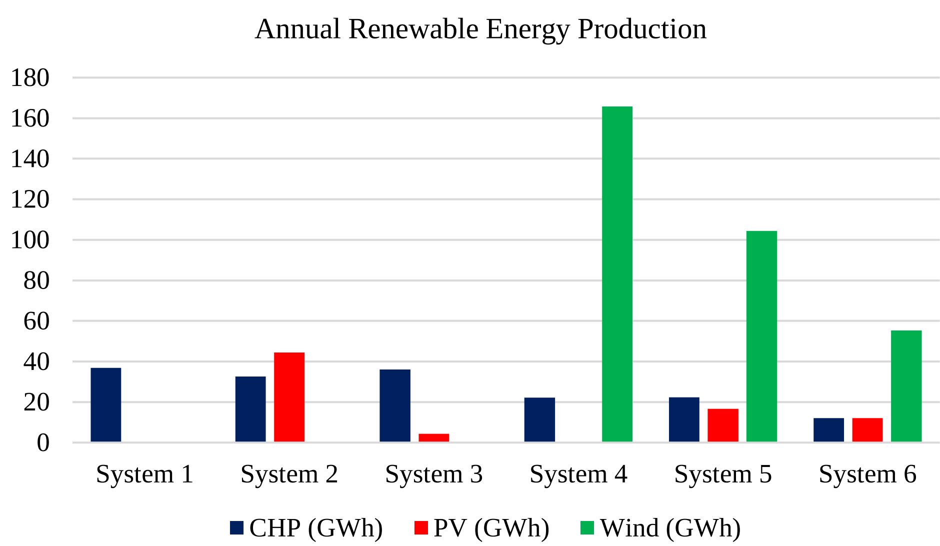


Figure 6.15 Annual renewable electric production for all proposed systems

6.3 Multi-Objective Optimization: Case Study

The College of Yanbu, located in Yanbu, Saudi Arabia, is the focus of this case study. Yanbu is renowned for its high average wind speeds of approximately 8 m/s, making it an ideal location for the installation of wind turbines. The selected building within the college has a peak load of 34 kW, with the utility grid serving as the primary source to meet this demand. In the simulation, a wind turbine is integrated with a diesel generator to reduce reliance on the utility grid. Conflicting objectives are optimized simultaneously to identify a set of Pareto front optimal solutions. Both the Original and Modified Firefly Algorithms (MFA) were used, and four scenarios of power source configurations were evaluated. The MFA consistently outperformed the Original FA when it came to reducing Net Present Costs (NPCs) and improving Levelized Cost of Energy (LCOE), while maintaining or improving reliability under all circumstances.

- Scenario 1: Utility grid, 6 kW Wind power, and 1 kW Diesel generator

Using Scenario 1 (Figure 6.16 a and b), in which the MFA is integrated with a 6-kW wind turbine combined with a 1 KW diesel generator, the NPC of the system is reduced by a significant percentage compared with that of the Original FA, demonstrating the efficiency of the MFA.

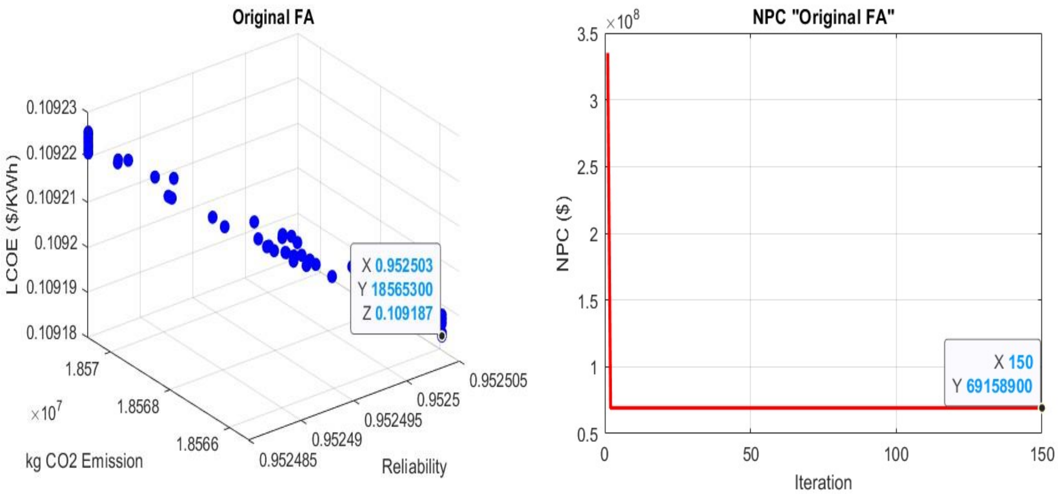


Figure 6.16a MFA-Scenario 1: Tradeoff of LCOE, CO_2, Reliability, and NPC

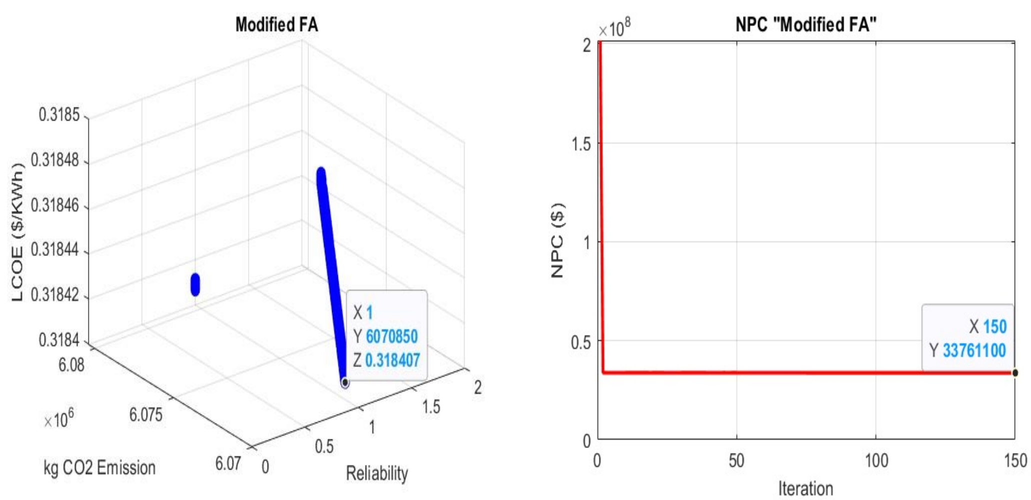


Figure. 6.16b MFA-Scenario 1: Tradeoff of LCOE, CO_2, Reliability, and NPC

- Scenario 2: Utility grid, 6 kW Wind power

MFA demonstrated a greater reduction in costs and improvement in environmental metrics than the Original FA in Scenario 2 (Figure 6.17 a and b).

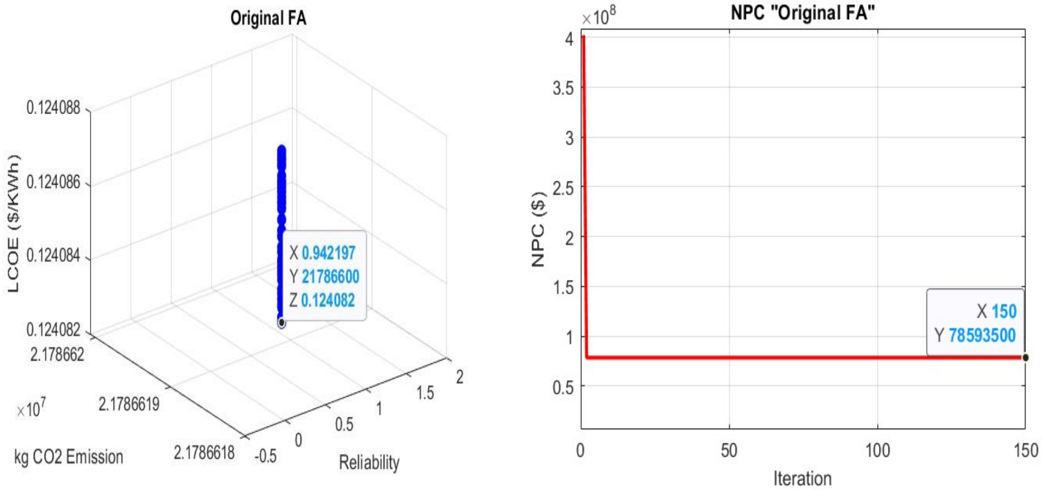


Figure. 6.17a MFA-Scenario 2: Tradeoff of LCOE, CO_2, Reliability, and NPC

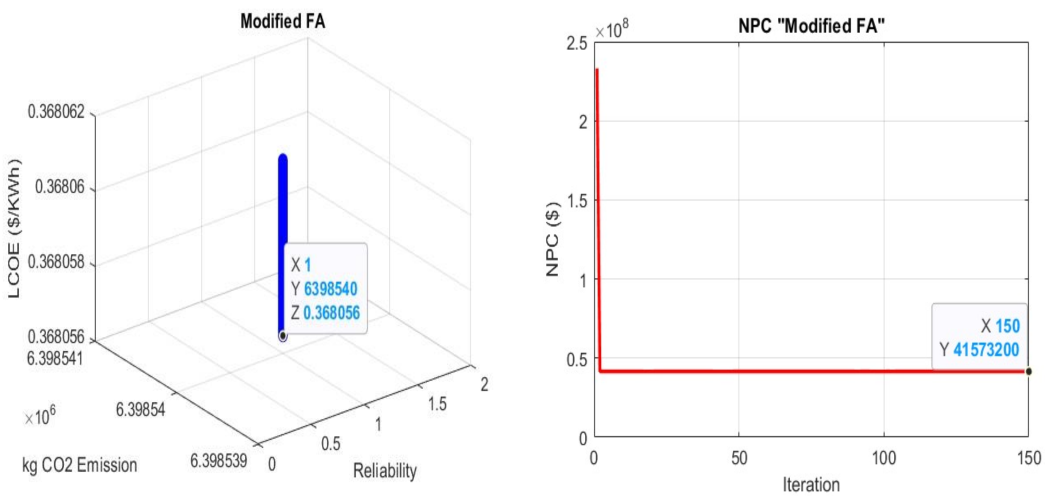


Figure. 6.17b MFA-Scenario 2: Tradeoff of LCOE, CO_2, Reliability, and NPC

- Scenario 3: Utility grid, 18 kW Wind power, and 1 kW Diesel generator

In Scenario 3 (Figures 6.18 a and b), which included wind turbines with 18 KW capacity and diesel generators with 1 KW capacity, the MFA continued to deliver better results than the Original FA.

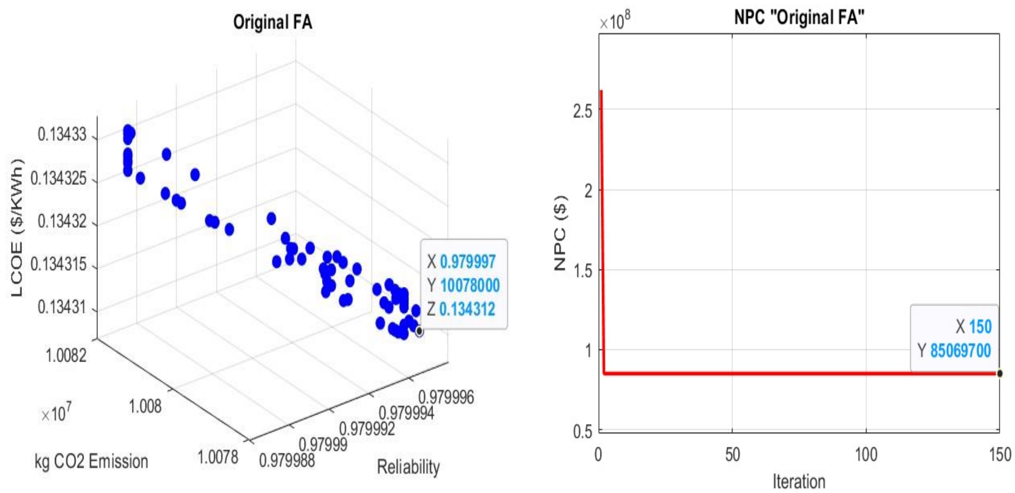


Figure. 6.18a MFA-Scenario 3: Tradeoff of LCOE, CO_2, Reliability, and NPC.

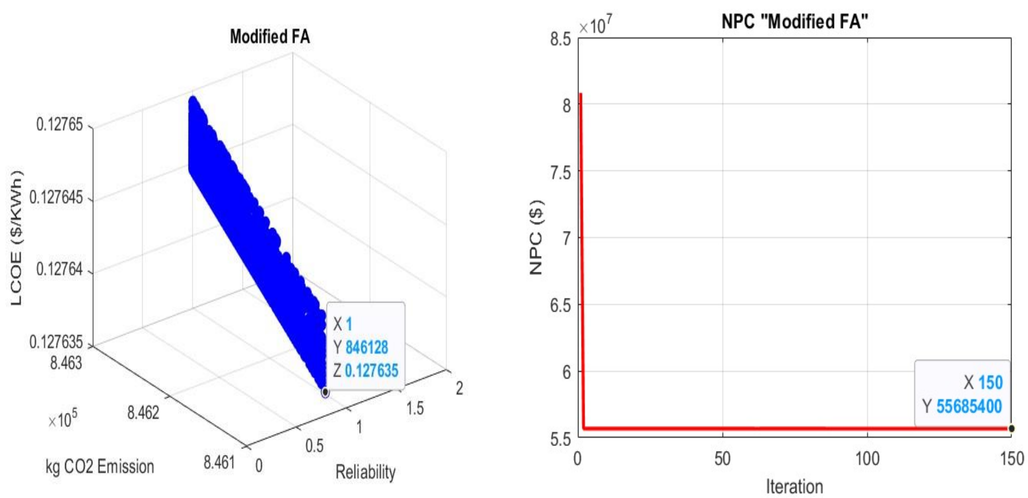


Figure. 6.18b MFA-Scenario 3: Tradeoff of LCOE, CO_2, Reliability, and NPC

- Scenario 4: Utility grid, 18 kW wind power

In Scenario 4 (Figure 6.19 a and b), in which the grid is paired with an 18 KW wind turbine, the MFA demonstrated its superior performance in systems that rely solely on renewable resources.

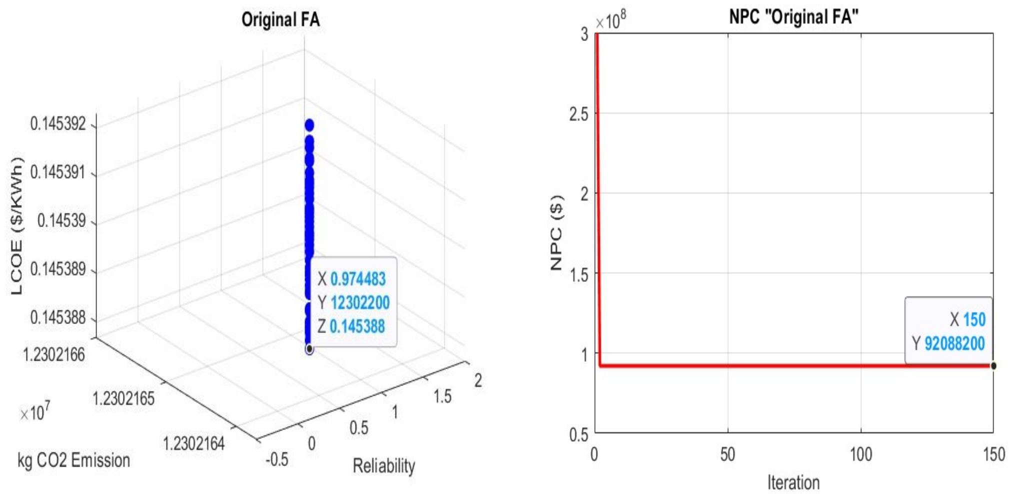


Figure. 6.19a MFA-Scenario 4: Tradeoff of LCOE, CO_2, Reliability, and NPC

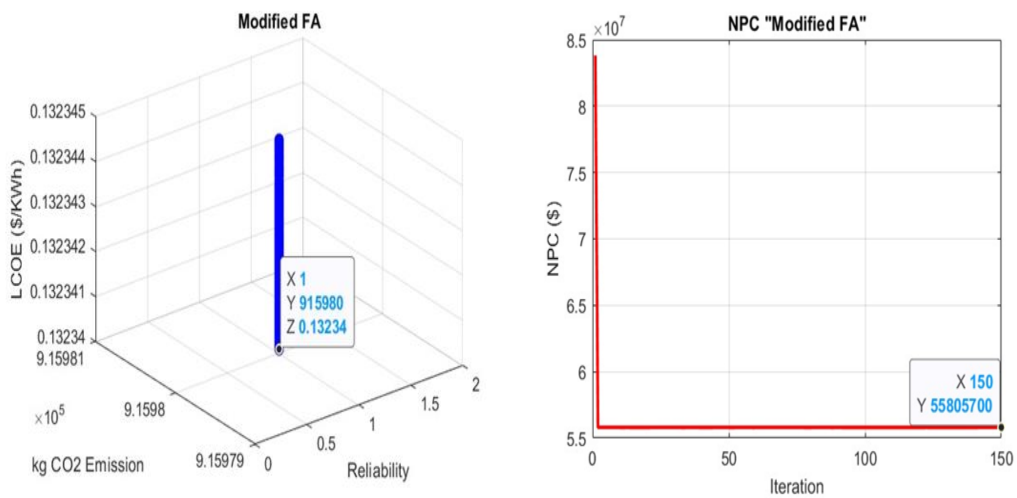


Figure. 6.19b MFA-Scenario 4: Tradeoff of LCOE, CO_2, Reliability, and NPC

6.3.6 Summary of All Scenarios' Results

Overall, the MFA demonstrated superior performance across all scenarios through cost reductions and environmental enhancements, exceeding the Original FA in key multi-objective metrics, such as NPC, LCOE, CO_2 emission, and reliability, as shown in Table 6.2. Multi-objective optimization of a hybrid energy system demonstrated considerable improvements over the traditional Firefly Algorithm (FA) on several performance aspects, including Net Present Cost, Levelized Energy Cost, CO_2 emissions, and system reliability. MFA showed a tradeoff between some objectives improving significantly and others deteriorating since the optimization process simultaneously considers multiple objectives.

Table 6.2 Comparison of the results obtained with FA and MFA

Scenario	Power source	Multi-Objectives							
		NPC ($)		LCOE ($/KWh)		CO_2 Emission (Kg)		Reliability	
		FA	MFA	FA	MFA	FA	MFA	FA	MFA
1	Grid, 6KW wind and 1KW DG	69158900	33761100	0.11	0.3	18565300	3070850	0.95	1
2	Grid and 6KW wind	78593500	41573200	0.12	0.36	21786600	6398540	0.94	1
3	Grid, 18 KW wind and 1KW DG	85069700	55685400	0.13	0.12	10078000	8461208	0.97	1
4	Grid and 18KW wind	92088200	55805700	0.14	0.13	12302200	9159180	0.97	1

Across all scenarios, MFA consistently reduced NPC, achieving reductions of 34.5% to 51.2%, indicating that it is a more cost-effective energy solution. Nevertheless, MFA demonstrated some increase in the LCOE in scenarios 1 and 2, illustrating its effectiveness in reducing environmental impact. Even with a higher LCOE, MFA was able to reduce CO_2 emissions by 16% to 83.5%. Additionally, MFA demonstrated consistent reliability improvements, achieving 100% reliability across all scenarios, whereas FA achieved reliability ranges between 94% and 97%. MFA offers a more balanced optimization solution that reduces costs and emissions while enhancing reliability, resulting in an overall improvement of approximately 16 % over conventional FAs.

6.3.6 Performance evaluation of MFA

The performance metrics evaluation of Pareto solutions obtained from the Modified Firefly Algorithm (MFA) indicate a diverse set of optimal solutions across scenarios, as illustrated in Table 4. The Pareto front is characterized by a wide range of values, illustrating the variability of trade-offs achieved. In addition to minimum and maximum values, ranges, standard deviations, and means, the algorithm provides insight into its capability of exploring and balancing a variety of performance parameters effectively.

Table 6.3 Performance metrics evaluation of Pareto solutions obtained by MFA

Scenario	Metrics	Min.	Max.	Range	STD.	Mean
Scenario 1	LCOE	0.0534	0.3184	0.2650	0.0261	0.0552
	Reliability	0.9850	1	0.0150	0.0012	0.9851
	CO_2 Emission	1.3065	6.07009	4.76	0.389	1.34
Scenario 2	LCOE	0.0656	0.368	0.3024	0.0242	0.0677
	Reliability	0.9828	1	0.0172	0.0014	0.9829
	CO_2 Emission	0.96	6.3985	5.4369	0.4439	0.99
Scenario 3	LCOE	0.0879	0.1276	0.0397	0.0032	0.0882
	Reliability	0.997	1	0.0023	0.0002	0.9978
	CO_2 Emission	1.319	8.4614	7.1415	0.5831	1.3681
Scenario 4	LCOE	0.08881	0.1323	0.0442	0.0036	0.0884
	Reliability	0.9975	1	0.0025	0.002	0.9975
	CO_2 Emission	1.2073	9.159	7.9525	0.6493	1.2610

6.4 Adaptive MPC and Multi-Level Control: Case Study

The current system at Oakland University is powered by the utility grid and a 4.5 MW CHP substation. To enhance control and efficiency in this case study, solar PV, wind turbines (WT), and energy storage systems (ESS) will be integrated into the system. A MATLAB framework, incorporating adaptive Model Predictive Control for real-time adjustment, was employed to develop a multi-level control strategy for the proposed microgrid. This setup was essential to ensure robust communication between control units. In this configuration, the power outputs of each distributed energy resource (DER) were utilized by AMPC to optimize the overall performance of the microgrid system. The controller was tested across four seasons, with the selected day being the highest in load consumption across the campus, and the results were compared to those of the basic MPC

6.4.1 Meteorological data and Load demand

Meteorological data, specifically solar irradiation, ambient temperature, and wind speed played a crucial role in the simulation of the proposed multi-level control strategy, which incorporated Adaptive Model Predictive Control (AMPC). Data were obtained from the National Renewable Energy Laboratory (NREL), ensuring that environmental conditions were accurately represented. A load demand profile for the year 2023 was also provided by Oakland University's Facility Management Department.

The controller was simulated on dates that have historically experienced peak load levels for each season, thus providing an in-depth framework for assessing its adaptability to different climate scenarios. As a result of these particular dates, it is possible to demonstrate the control system's ability to cope with variations in load demand, temperature, solar irradiance, and wind speed throughout the year. The following sections will discuss the results obtained for each season, providing insight into the dynamic operation of the system under varying environmental conditions.

- Winter

  In Winter, irradiance is slightly over 200 W/m² during the midday that cause in reducing the generated power from the solar panels to 0W, as the temperature at freezing level as in Figure 6.20. The average wind speed is 5 m/s that provide an optimal solution for the operation of wind-turbines. The load contributes to the maximum electrical load during midday, according to the generated schedule, at a level of 5,500 kW.

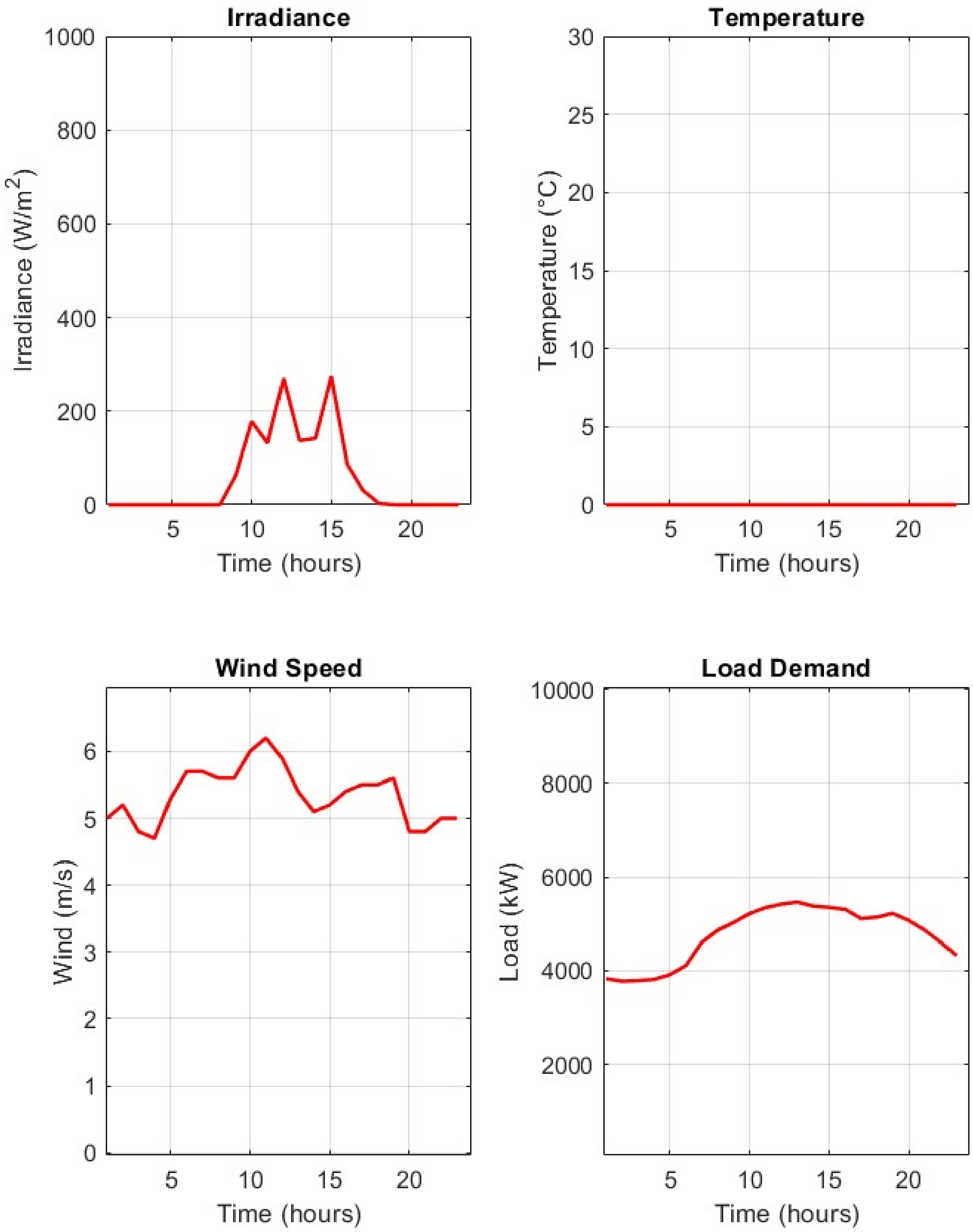


Figure 6.20 Daily Profiles of Meteorological data and Load Demand in Winter

- Spring

  Enhances the sunlight intensity to over 900 W/m^2 to increase solar power output. A relatively low temperature is ideal for operation of PV's. They include inadequate wind which reduces the generation of wind energy as Figure 6.21 shows. The load operates within a range, peaking at approximately 6,000 kW during the middle of the day.

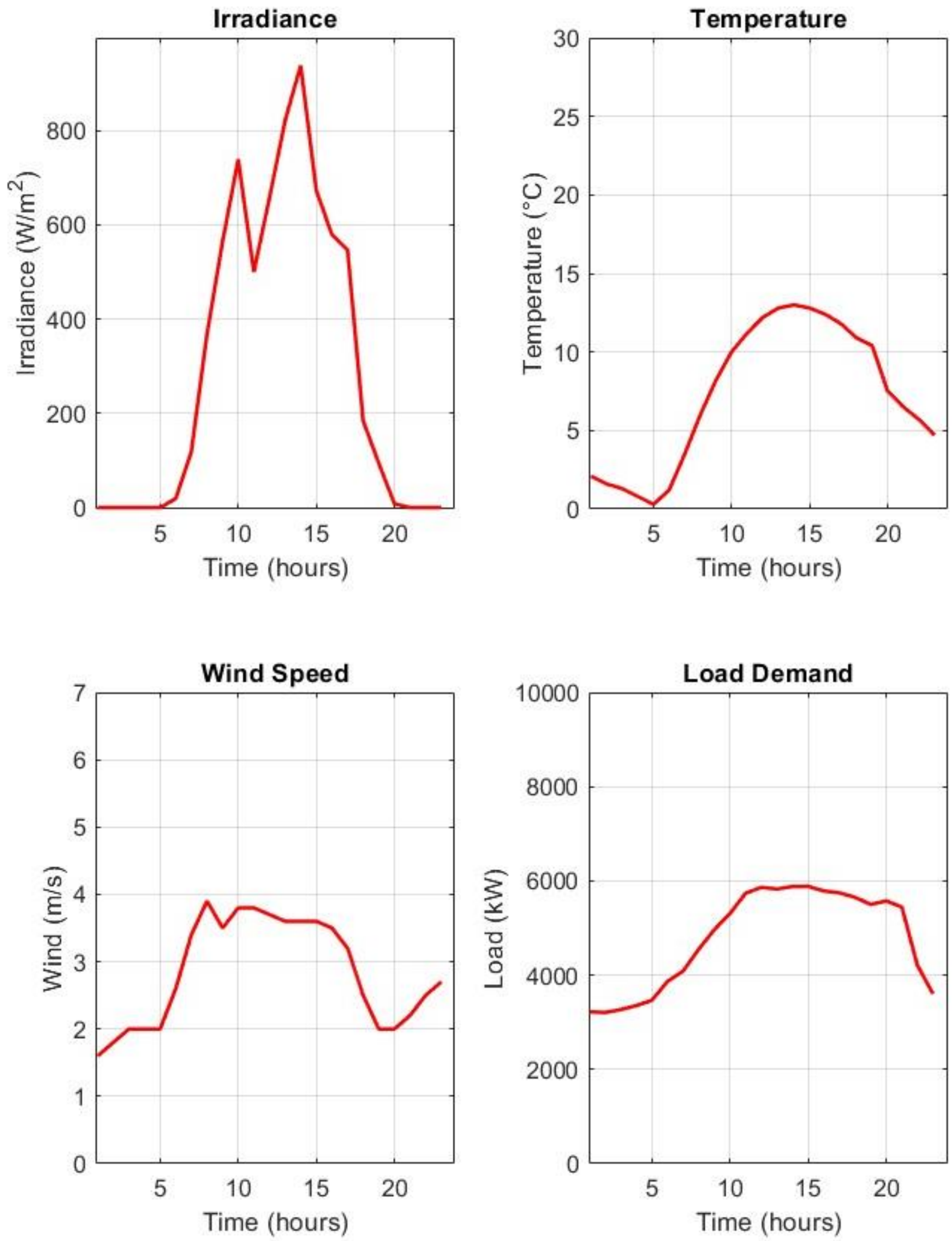


Figure 6.21 Daily Profiles of Meteorological data and Load Demand in Spring

- Summer

  The summer Figure 6.22 illustrates the irradiance is slightly over 800 W/m^2, which generates power from the solar panels, as the temperature is nearly 25°C in the middle of the day. The average wind speed is 2 m/s, making the wind energy insufficient. Power consumption rises throughout the day, peaking at 7,000 kW due to the cooling system.

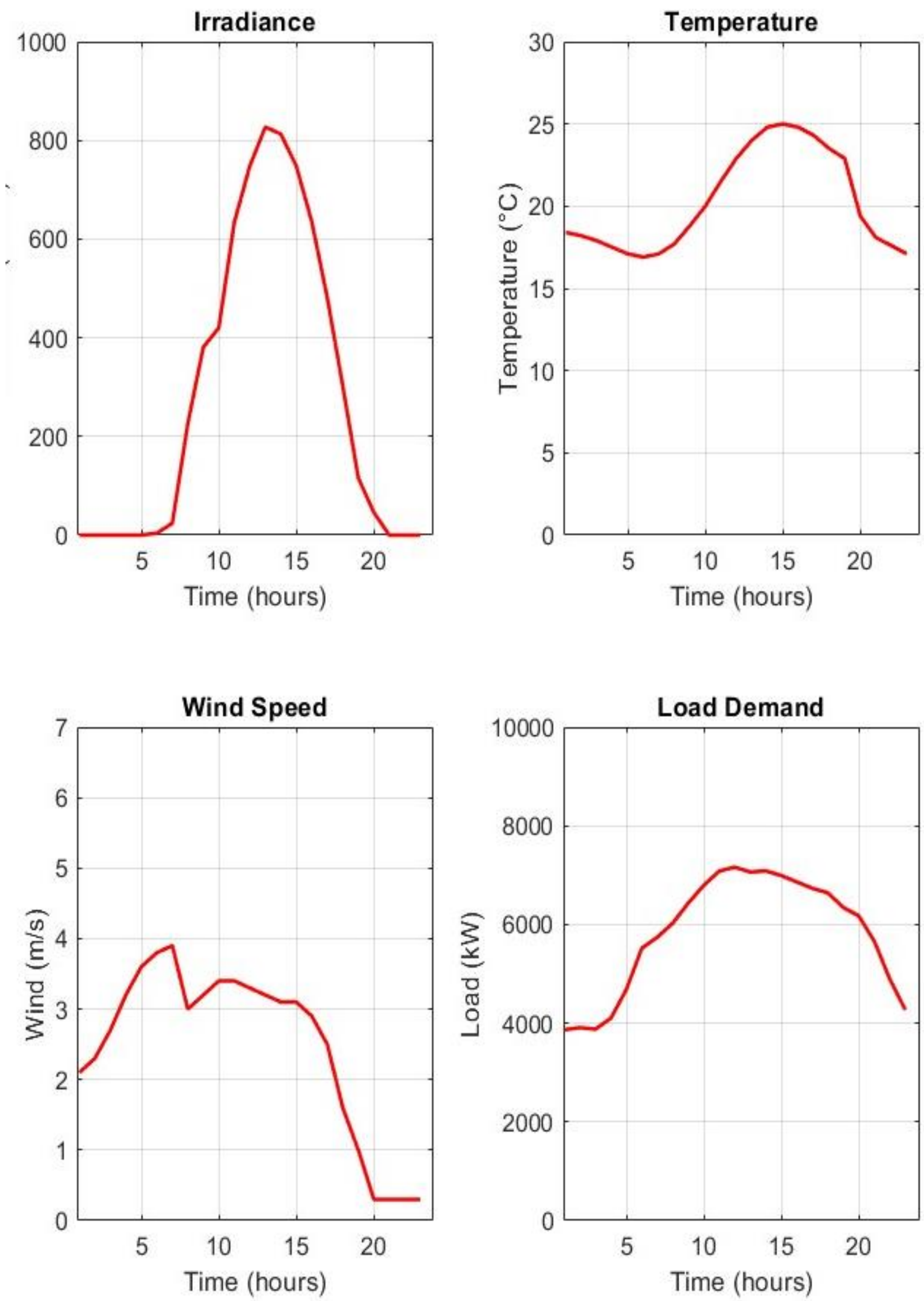


Figure 6.22 Daily Profiles of Meteorological data and Load Demand in Summer

- Fall

  In Fall, Figure 6.23 shows the conditions are satisfactory due to the high irradiance, slightly over 800 W/m^2, and temperatures at approximately 26°C in late afternoon. Optimal wind speeds that can yield significantly high amounts of energy occur at a wind speed average of approximately 2.5 m/s. The load has exceeded 9,000 kW due to the full attendance of students and staff.

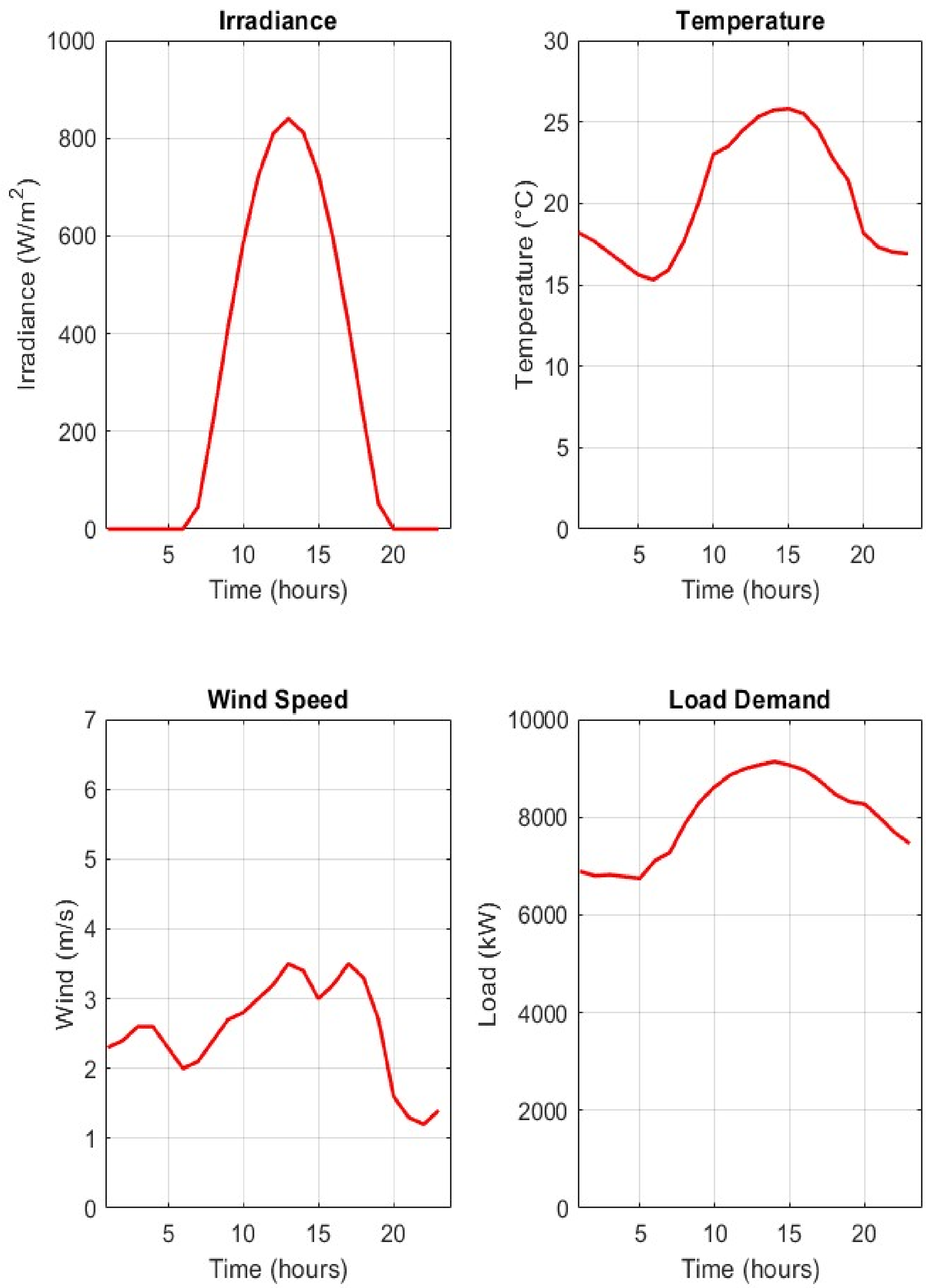


Figure 6.23 Daily Profiles of Meteorological data and Load Demand in Fall

6.4.2 The Comparative Power Output Profiles Across Seasons

An analysis of the power output of solar, wind, and combined heat and power in the winter, spring, summer, and fall is presented here. As the subsequent control action is carried out after appropriate data has been gathered from the DERs in real time, the outcome of the DERs will have a bearing on the first control level of the adaptive multi-level control scheme.

- Winter

  The Winter Analysis Figure 6.24 shows that no solar power output throughout the day, which is typical for the winter season when solar irradiation can be extremely low, and the solar panels may be covered by snow or frost. The wind power output exhibits some fluctuation, indicating variability in wind speeds during the day. The CHP maintains a relatively stable output, demonstrating its role as a dependable source of power to compensate for the unreliability of solar power during this season.

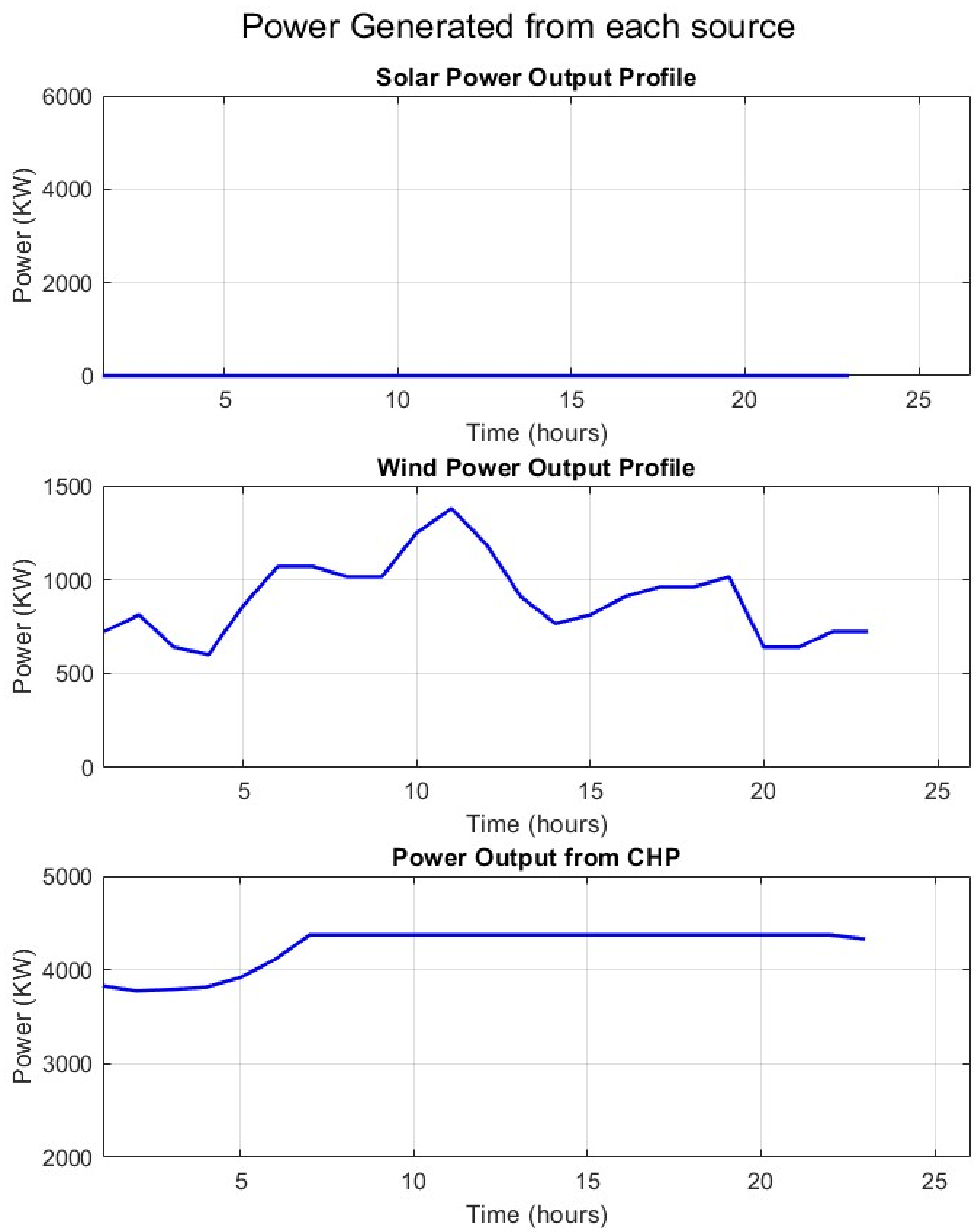


Figure 6.24 Comparative Power Output Profiles from PV, WT, and CHP in Winter

- Spring

  As Figure 6.25 shows, the solar power output profile reveals a mid-day peak, characteristic of better solar irradiation in spring compared to winter. This pattern shows the increased potential for solar energy generation as daylight hours extend. Wind power output remains relatively stable throughout the day, showing little variation, which indicates consistent wind conditions during this season. Meanwhile, the output from CHP shows a slight decline in the late hours, suggesting operational adjustments or reduced demand, yet it still provides a significant and stable contribution to the overall power mix, ensuring the system can meet load requirements efficiently.

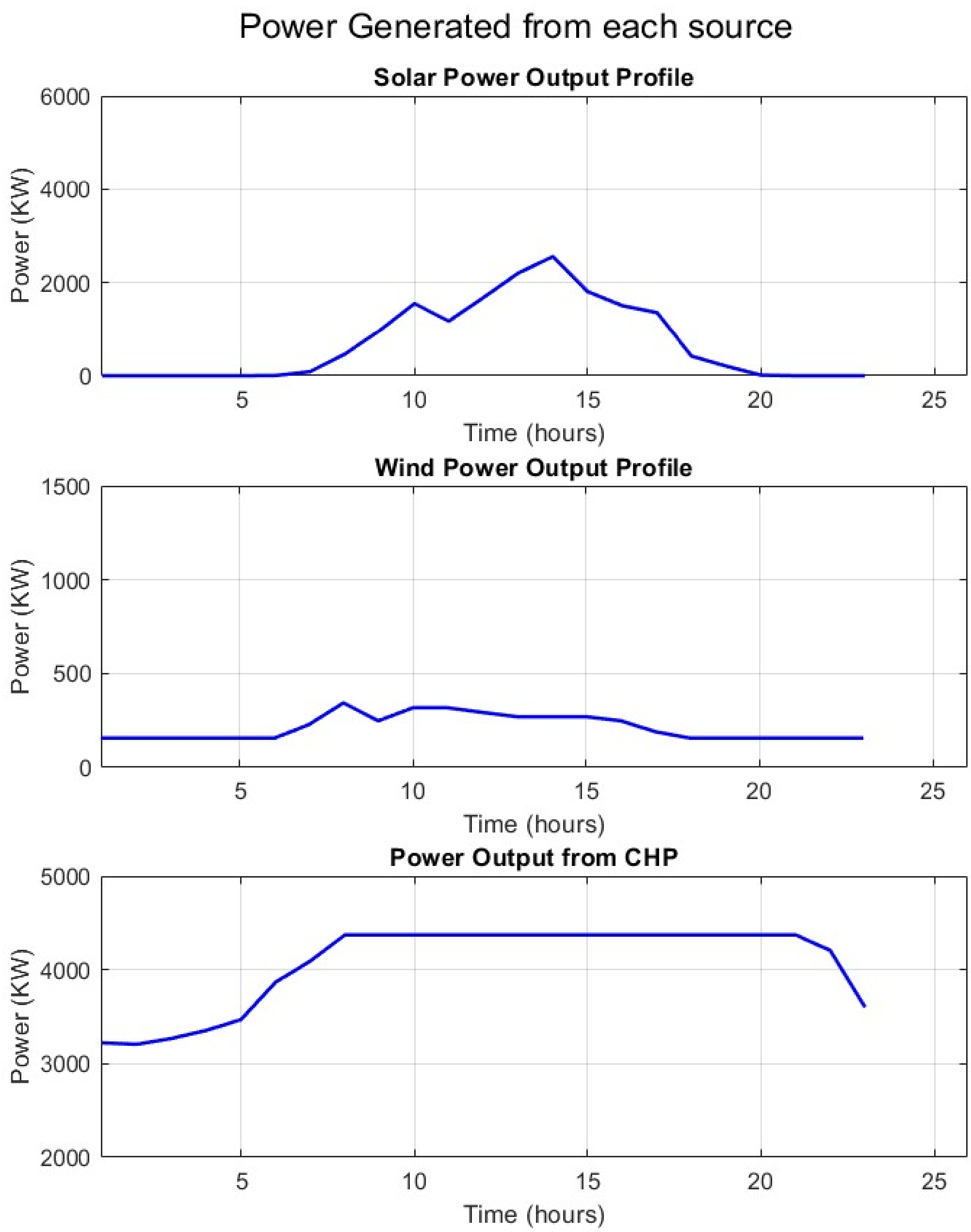


Figure 6.25 Comparative Power Output Profiles from PV, WT, and CHP in Spring

- Summer

  Figure 6.26 illustrates Solar power reaches its maximum around midday, which is characteristic of the intense solar irradiation during summer, providing a significant energy contribution. Wind power remains constant, though it shows a slight decrease, indicative of potentially lower wind speeds during these warmer months. The Combined Heat and Power (CHP) output starts below its usual capacity in the early morning but stabilizes shortly thereafter to maintain a nearly constant output, contributing reliably to the system’s base load requirements for most of the day.

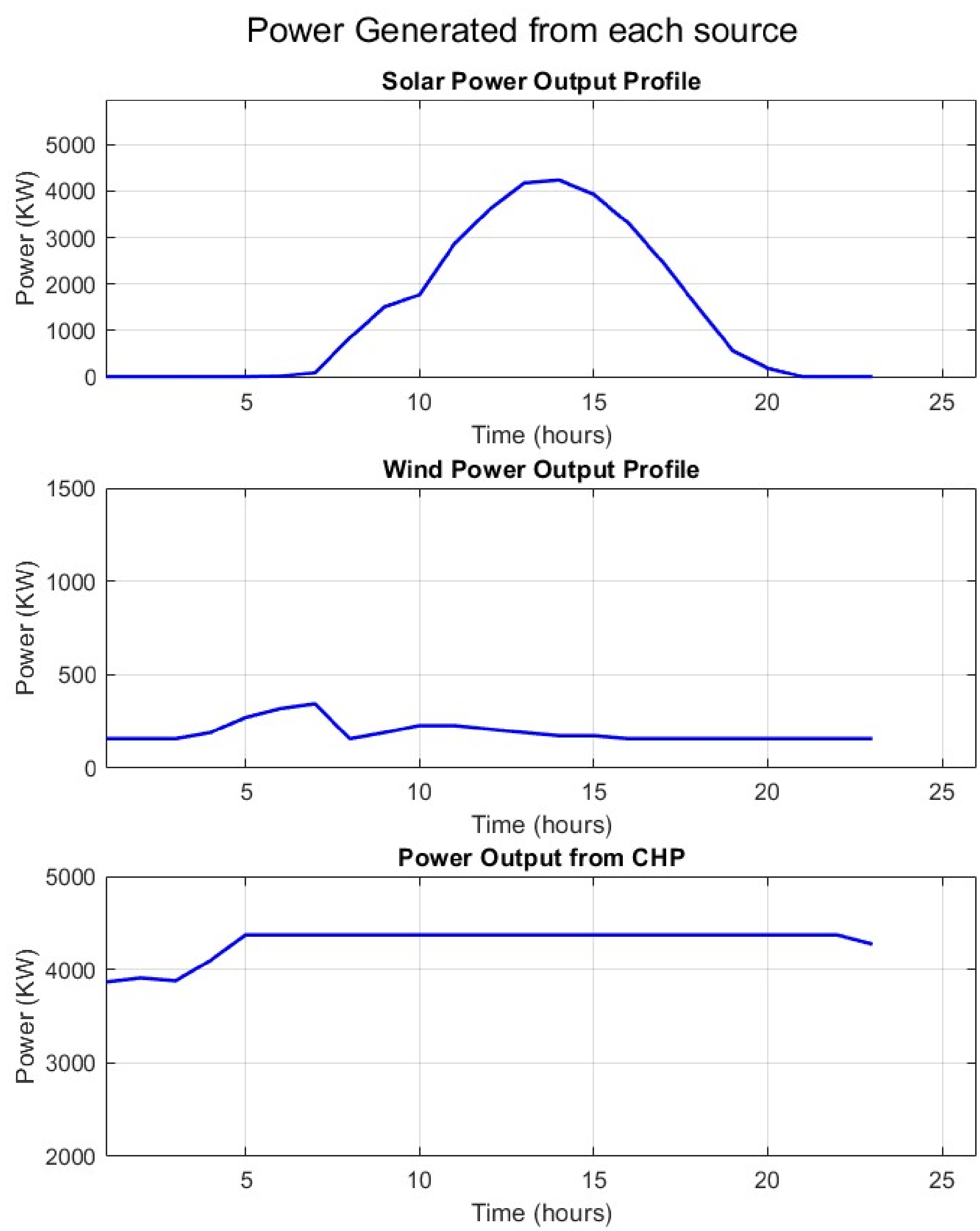


Figure 6.26 Comparative Power Output Profiles from PV, WT, and CHP in Summer

- Fall

  The characteristics of the Fall as shown Figure 6.27. Solar power exhibits a significant peak during the day, reflecting a decrease from summer levels but still indicating substantial solar energy capture, likely influenced by shorter days and lower sun altitude typical of fall. The wind power output remains stable with slight fluctuations, suggesting moderate but consistent wind conditions suitable for energy generation during this season. Contrary to the statement about varying CHP output, the graph shows that CHP output is constant throughout the day, maintaining a steady supply of power that likely meets a consistent base load demand.

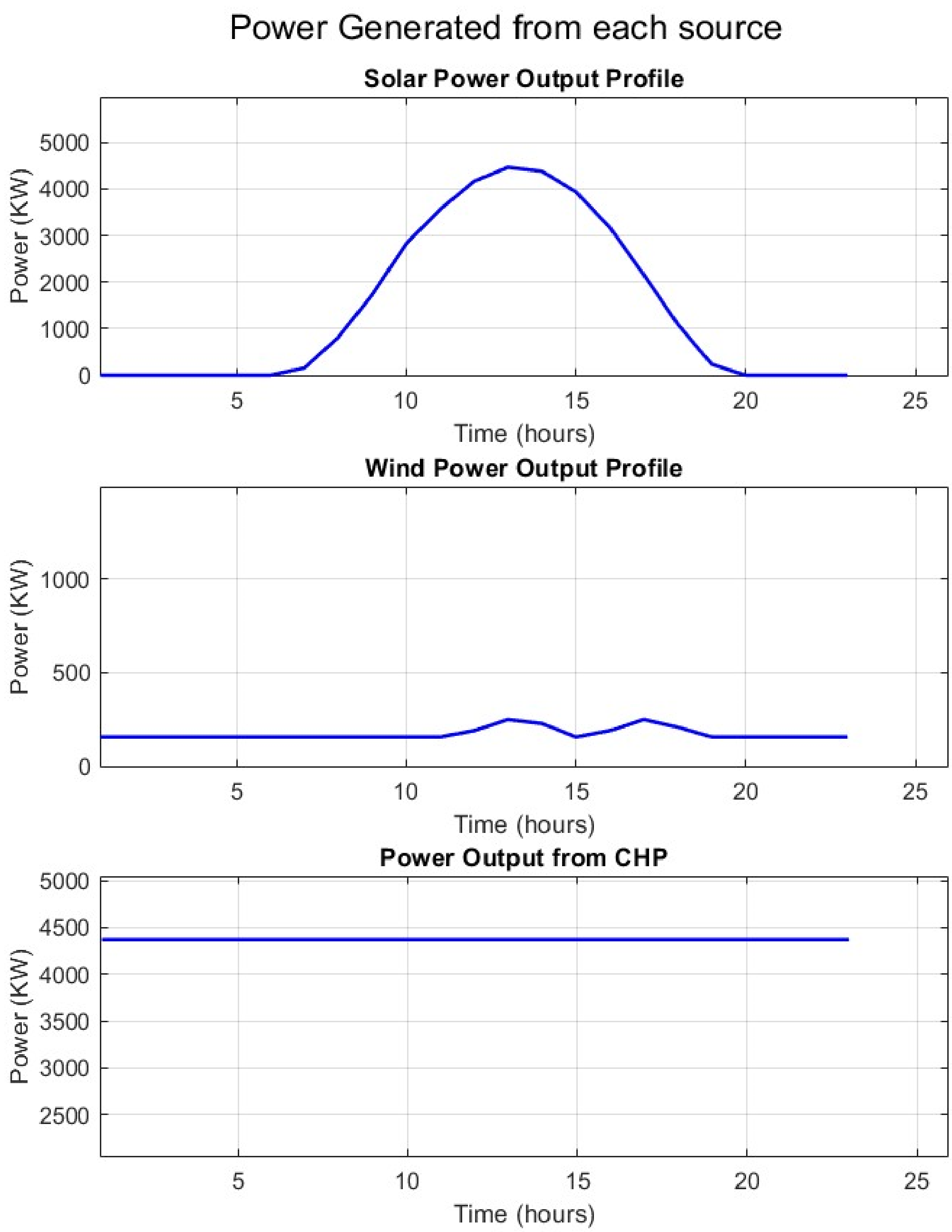


Figure 6.27 Comparative Power Output Profiles from PV, WT, and CHP in Fall

6.4.3 Operational Dynamics of Microgrids: From Generation to Battery Storage

In microgrid systems, it is essential to integrate renewable resources, for example, photovoltaic (PV) panels and wind generators, with power demand and grid energy to control diverse dynamics. "Adjusted" outputs in this context refer to the levels of power produced by these renewable sources as modified by specific real time depicted factors controlling the emission of real time production of energy. For example, there are efficiency losses in the use of PV caused by shading or changes in temperature, wind denial in wind turbines and limitations of the functioning of Combined Heat and Power systems.

A controller such as Adaptive Model Predictive Control (AMPC) is essential in the load control framework because it facilitates system balance and power sharing while mitigating uncertainties and actively responding to real environmental and load conditions. These adjustments and control measures significantly reduce the microgrid's dependence on the grid by ensuring that sufficient energy is available during periods of low renewable generation. Furthermore, the performance of the energy management process is enhanced by supplying net energy to the general supply and supporting the CHP systems under varying conditions. The results obtained from AMPC will be compared to those from basic MPC to demonstrate its superior performance.

6.4.3.1 Results Obtained with Basic MPC

- Winter

The analysis reveals that solar power generation is at 0 W during the winter season, not just low, which significantly impacts the overall energy supply. The load is primarily supplied by wind turbines (WT) and combined heat and power (CHP) systems; however, their combined output is insufficient to meet the total load demand, as shown in Figure 6.28. The graphs indicate that the grid is not supplying any additional power, highlighting a critical gap in energy management.

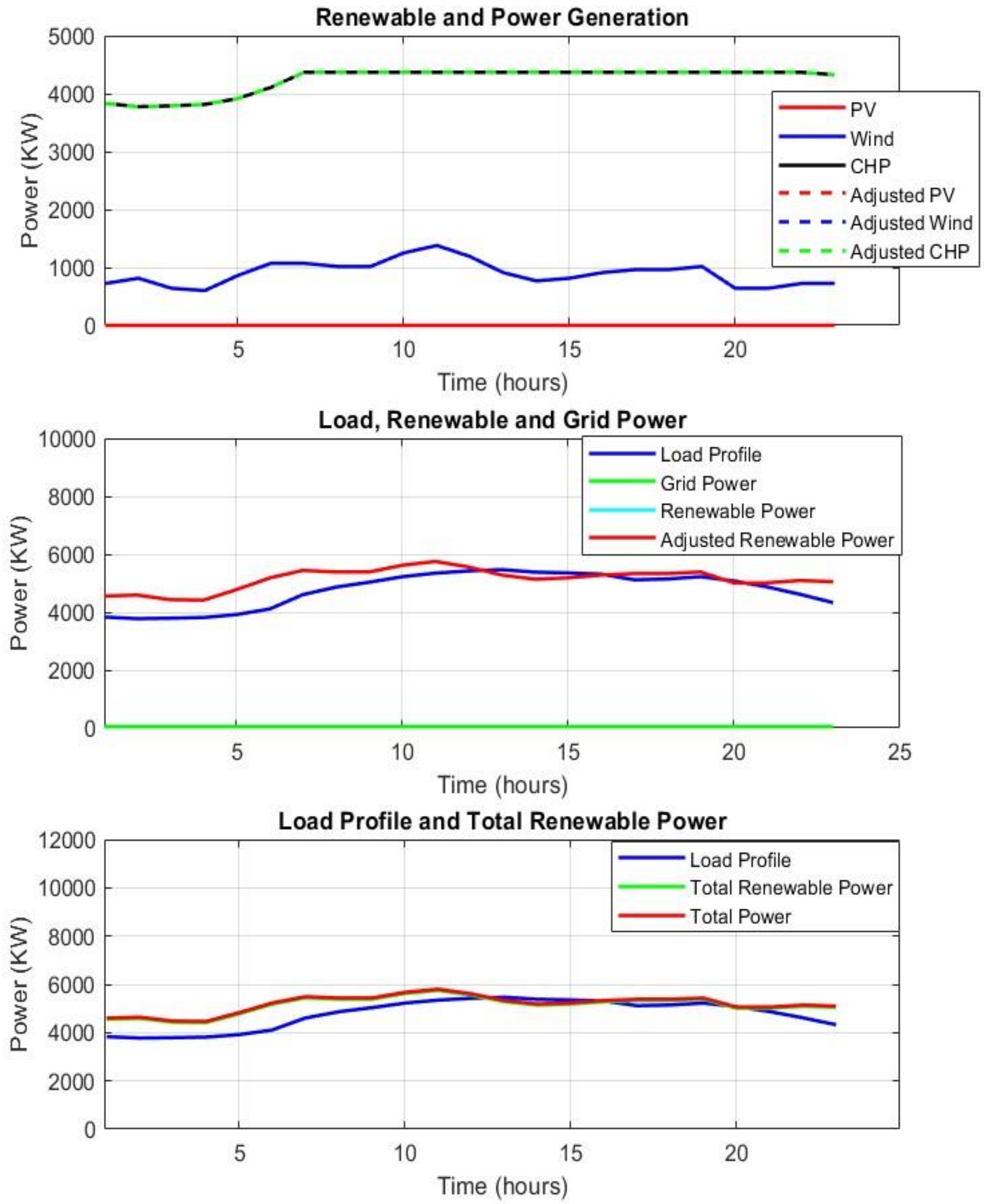


Figure 6.28 Load Profiles: Renewable vs. Grid Power Over 24 Hours in Winter

The analysis of the energy storage system (ESS) during the winter season reveals that, despite the load demand being unmet, the ESS remains fully charged throughout the observed period, as shown in Figure 6.29. The battery state of charge (SOC) stays at 100%, indicating that the energy storage is not being utilized effectively. The failure of the ESS to supply power highlights a critical disconnect between the available energy storage and the actual load requirements, demonstrating the inefficiencies of the control strategy in adapting to real-time energy needs.

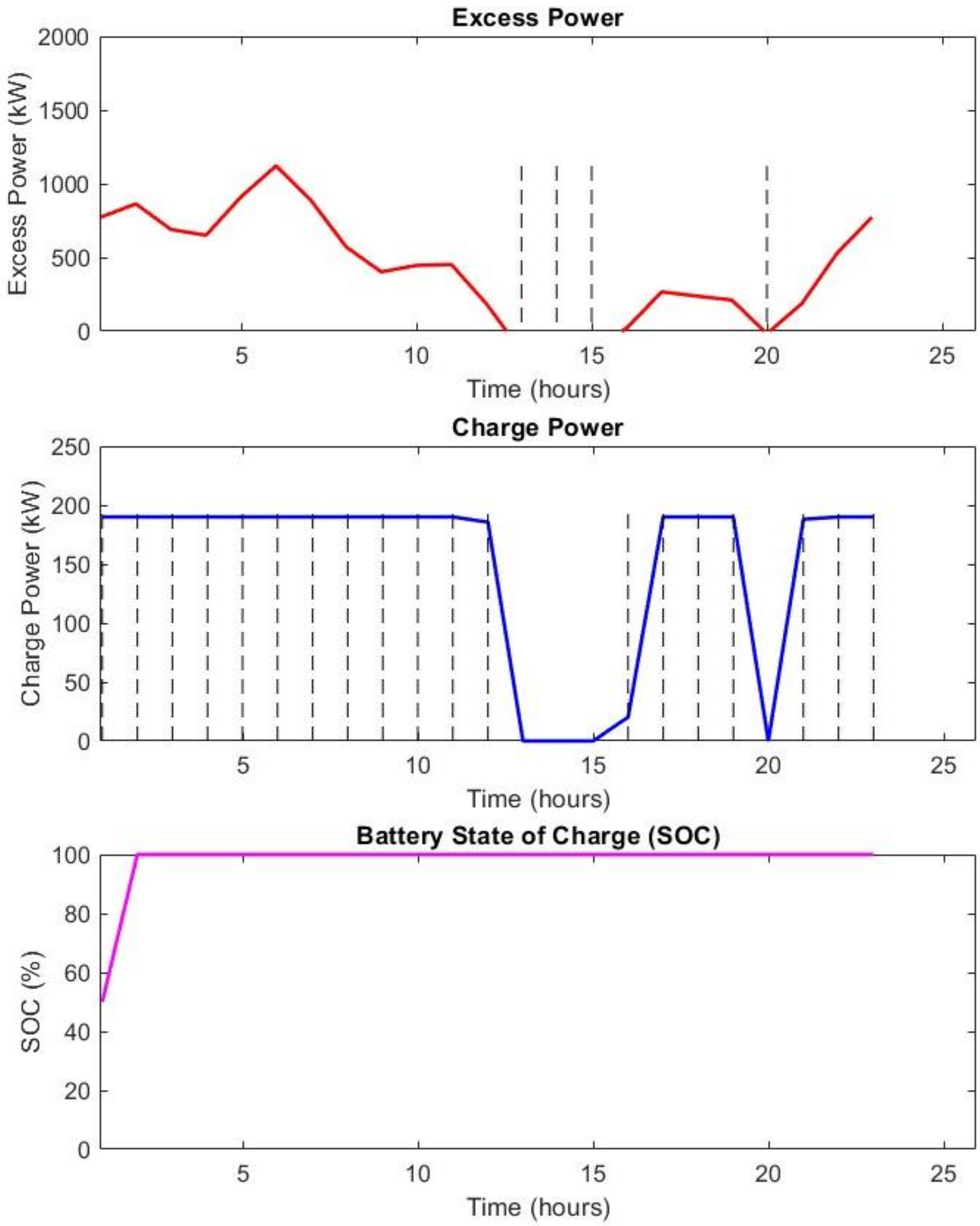


Figure 6.29 Dynamics of Excess Power, Charging Patterns, and SOC in Winter

- Spring

  The analysis of Figure 6.30 illustrates that during the spring season, there is minimal power generated from wind turbines (WT), while solar power generation exhibits a significant increase from around 7 AM to 7 PM, followed by a decrease in the evening. Despite the strong solar output, the load demand remains unmet, indicating a supply deficit.

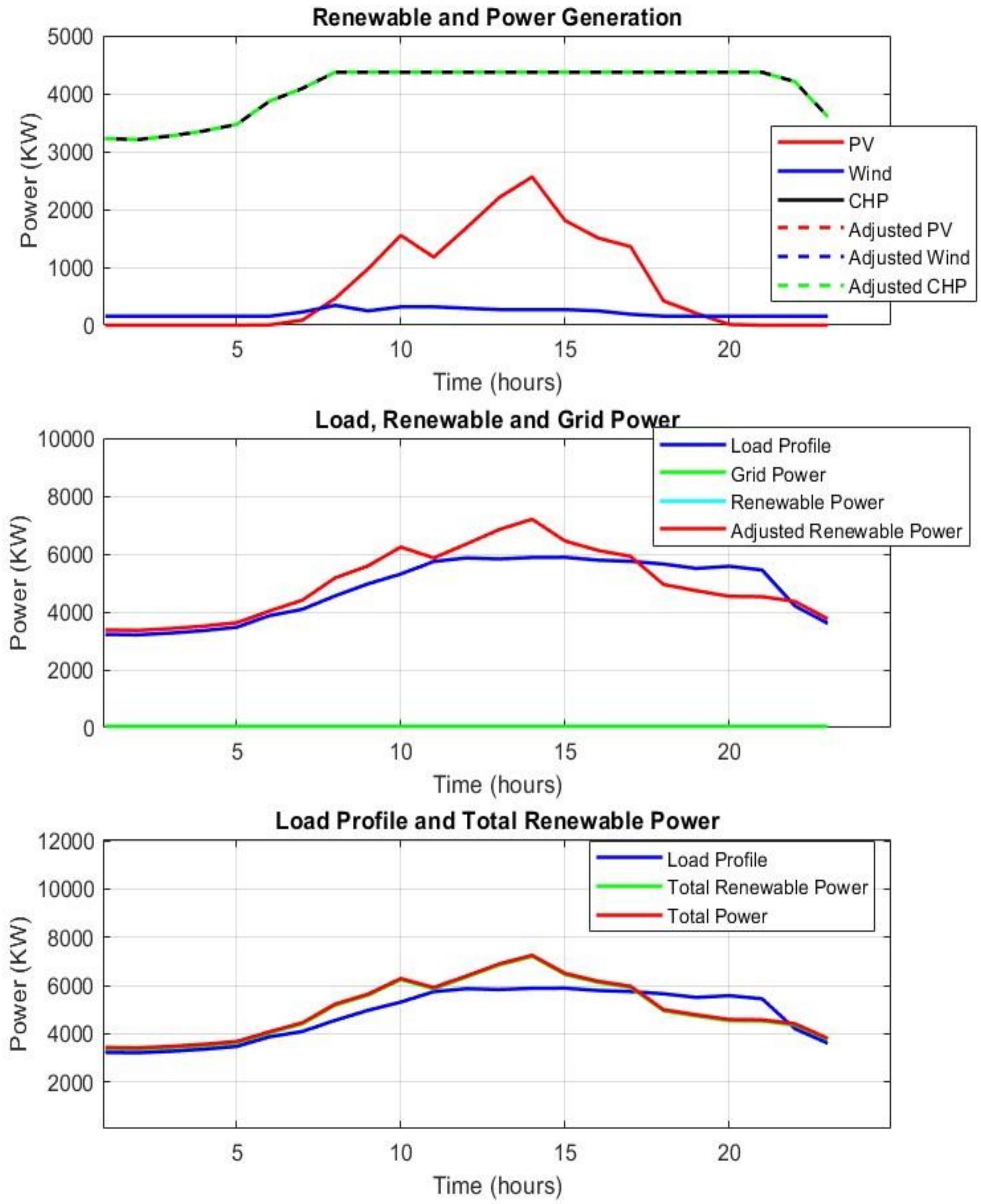


Figure 6.30 Load Profiles: Renewable vs. Grid Power Over 24 Hours in Spring

The analysis of Figure 6.31 illustrates the performance of the energy storage system (ESS) during the spring season. Throughout the observed period, there is a notable amount of excess power available, which successfully charges the battery storage to full capacity. However, the controller fails to discharge the ESS to supply the load when needed, resulting in a missed opportunity to meet the demand. This inefficiency indicates a critical limitation in the control strategy, as the stored energy is not utilized to address the load deficits despite being readily available.

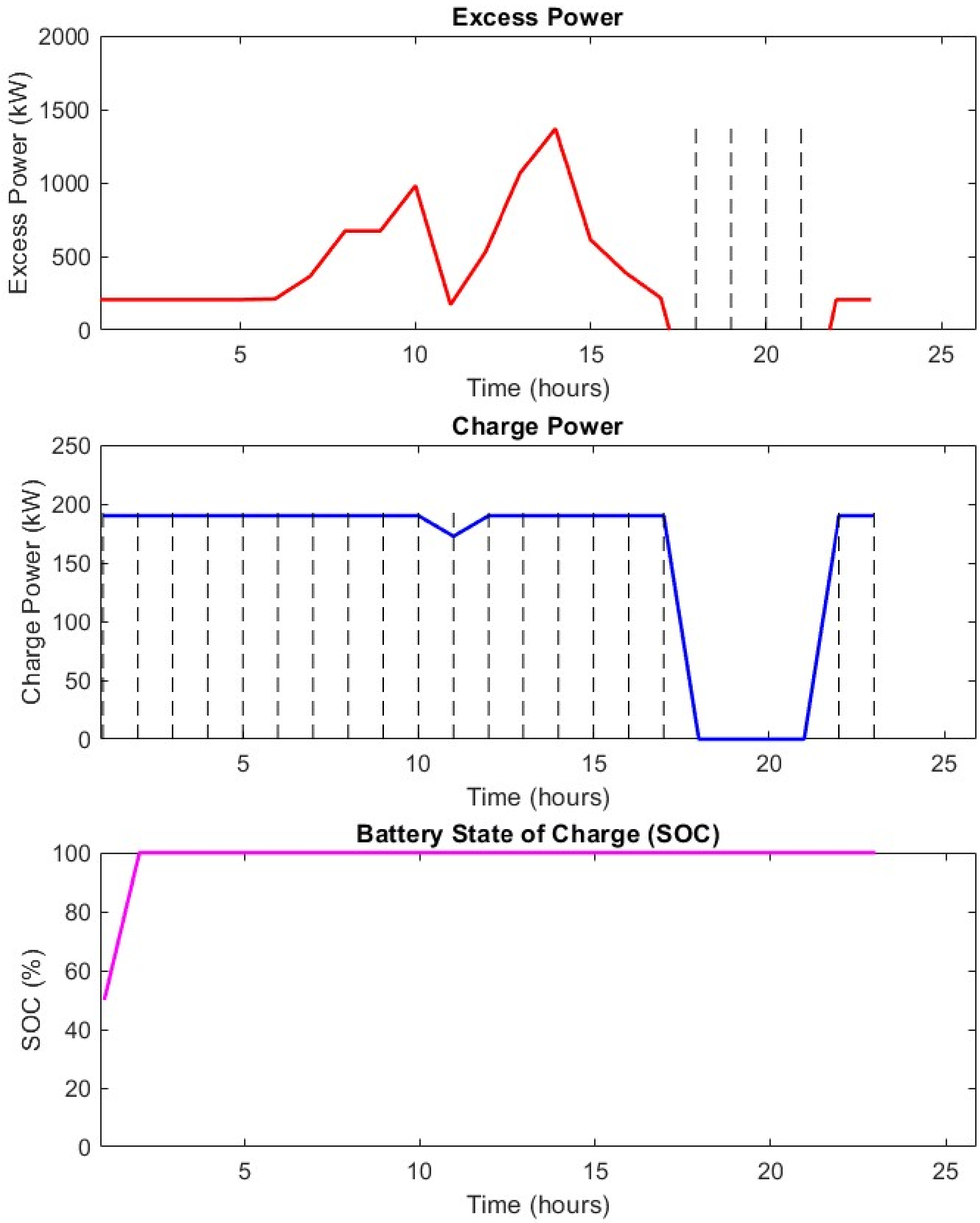


Figure 6.31 Dynamics of Excess Power, Charging Patterns, and SOC in Spring

- Summer

  The analysis of Figure 6.32 highlights the energy dynamics during the summer season, where the load demand is high and primarily supported by combined heat and power (CHP) systems, solar photovoltaic (PV) energy, and minimal contributions from wind turbines (WT). The load is met during the early morning hours, specifically from midnight to 5 AM, by a combination of CHP and minimal WT output. Solar power then effectively supports the load from 7 AM until 8 PM. However, between 5 AM and 10 AM, as well as from 7 PM until midnight, there are significant deficits in power supply. Notably, the grid is not utilized by the controller to address these deficiencies, resulting in an inability to meet the load demand during critical times when renewable generation falls short.

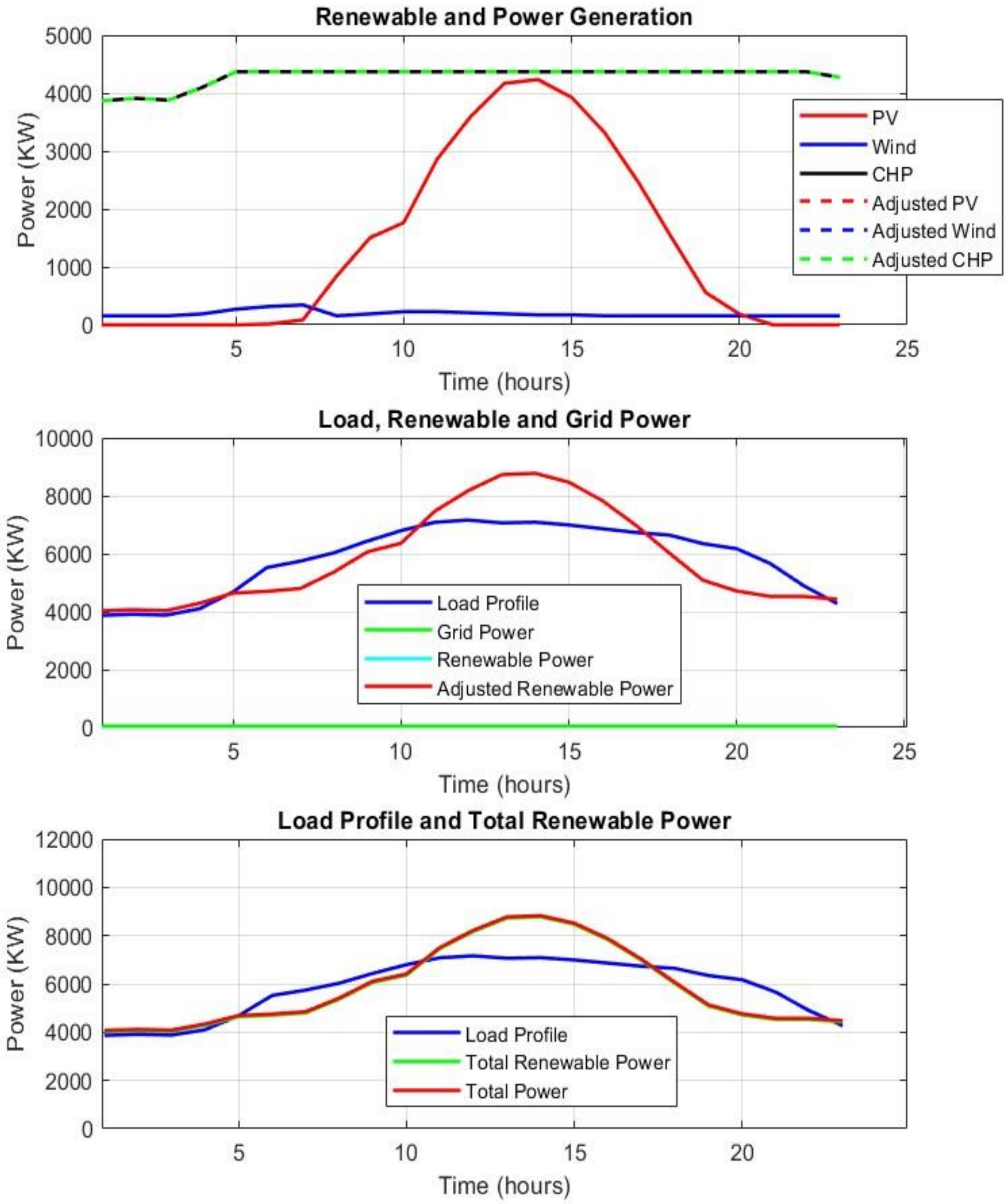


Figure 6.32 Load Profiles: Renewable vs. Grid Power Over 24 Hours in Summer

The analysis of Figure 6.33 for the energy storage system (ESS) during the summer season reveals that while there is significant excess power generated, the ESS remains underutilized. The plots indicate that excess power is available for charging the battery storage, yet the controller fails to discharge the ESS to supply the load when it is needed. As illustrated, the battery state of charge (SOC) remains at full capacity, suggesting that stored energy is not being deployed effectively to address demand peaks. This inefficiency highlights a critical limitation in the control strategy, as the system does not leverage the available energy storage to meet load requirements during periods of deficit.

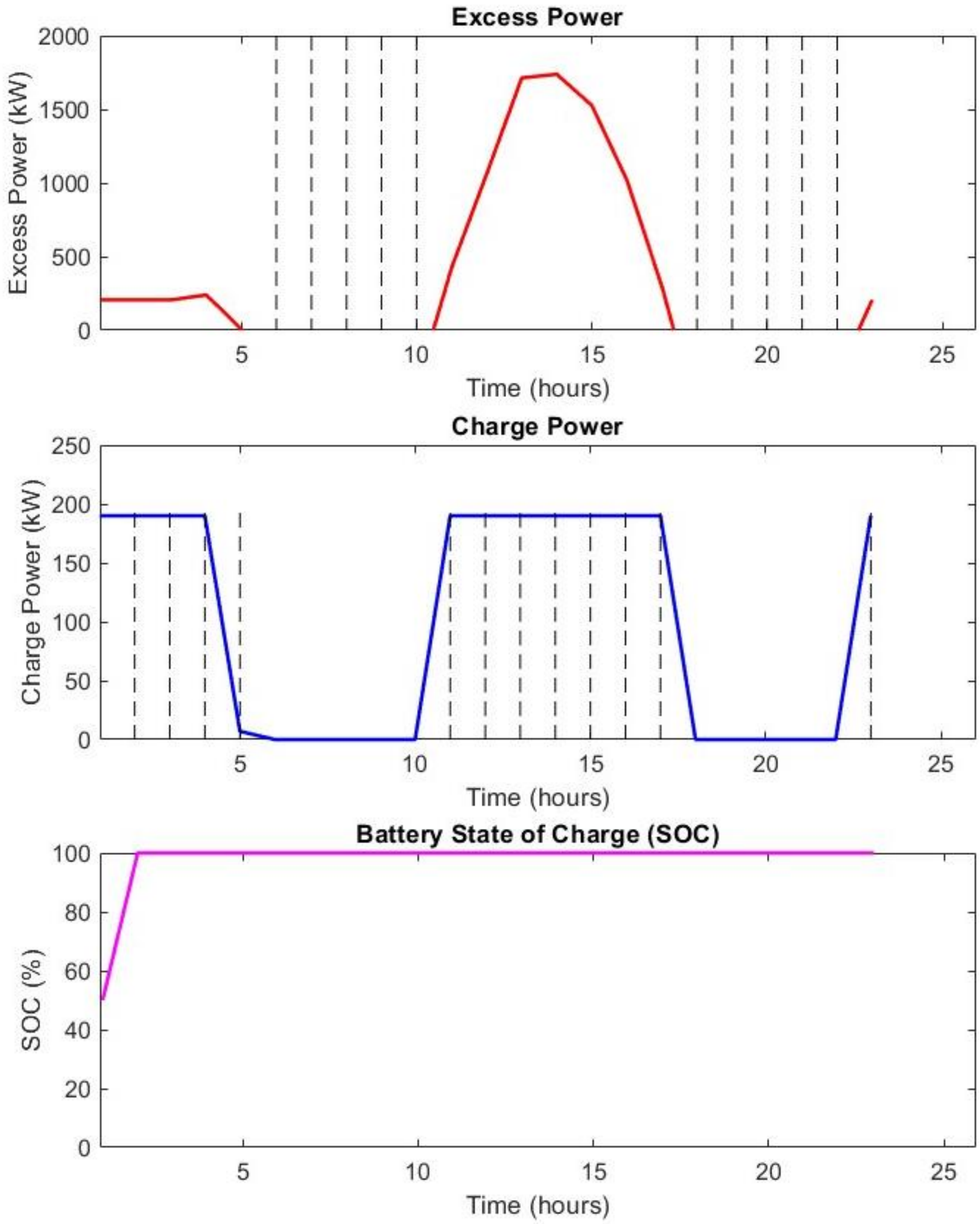


Figure 6.33 Dynamics of Excess Power, Charging Patterns, and SOC in Summer

- Fall

  The analysis of Figure 6.34 for the fall season reveals that solar power generation peaks during daylight hours, while wind power generation remains minimal. The load profile exhibits fluctuations, indicating varying demand throughout the day, which frequently exceeds the available renewable generation. The grid is not effectively utilized to meet these deficits when the load surpasses renewable supply.

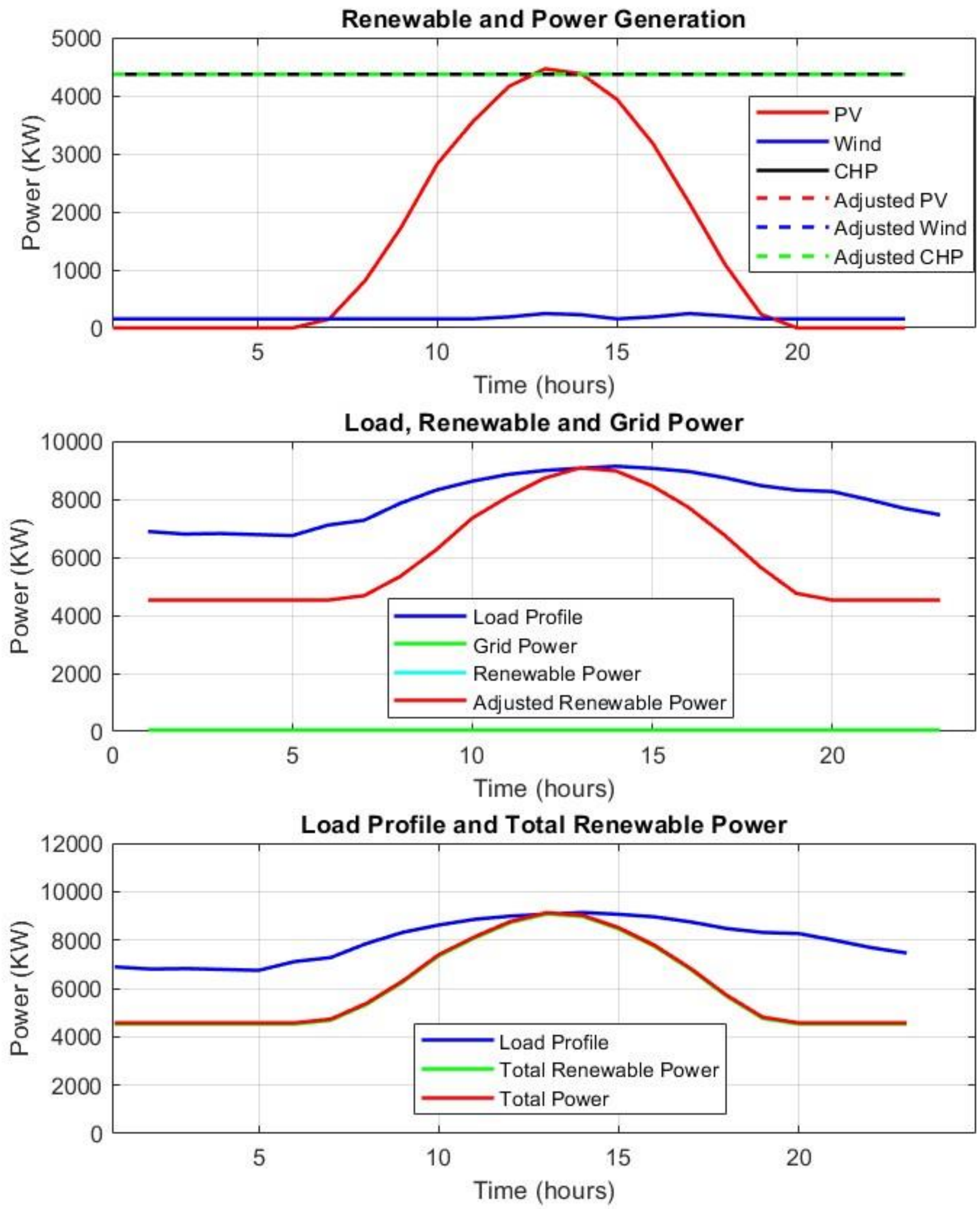


Figure 6.34 Load Profiles: Renewable vs. Grid Power Over 24 Hours in Fall

The analysis of Figure 6.35 for the energy storage system (ESS) during the summer season reveals critical performance issues. There is no excess power generated throughout the observed period, and the charge power plot indicates only a brief charging event. As a result, the battery state of charge (SOC) remains stable but underutilized, highlighting the control strategy's failure to effectively manage energy resources and meet fluctuating load demands.

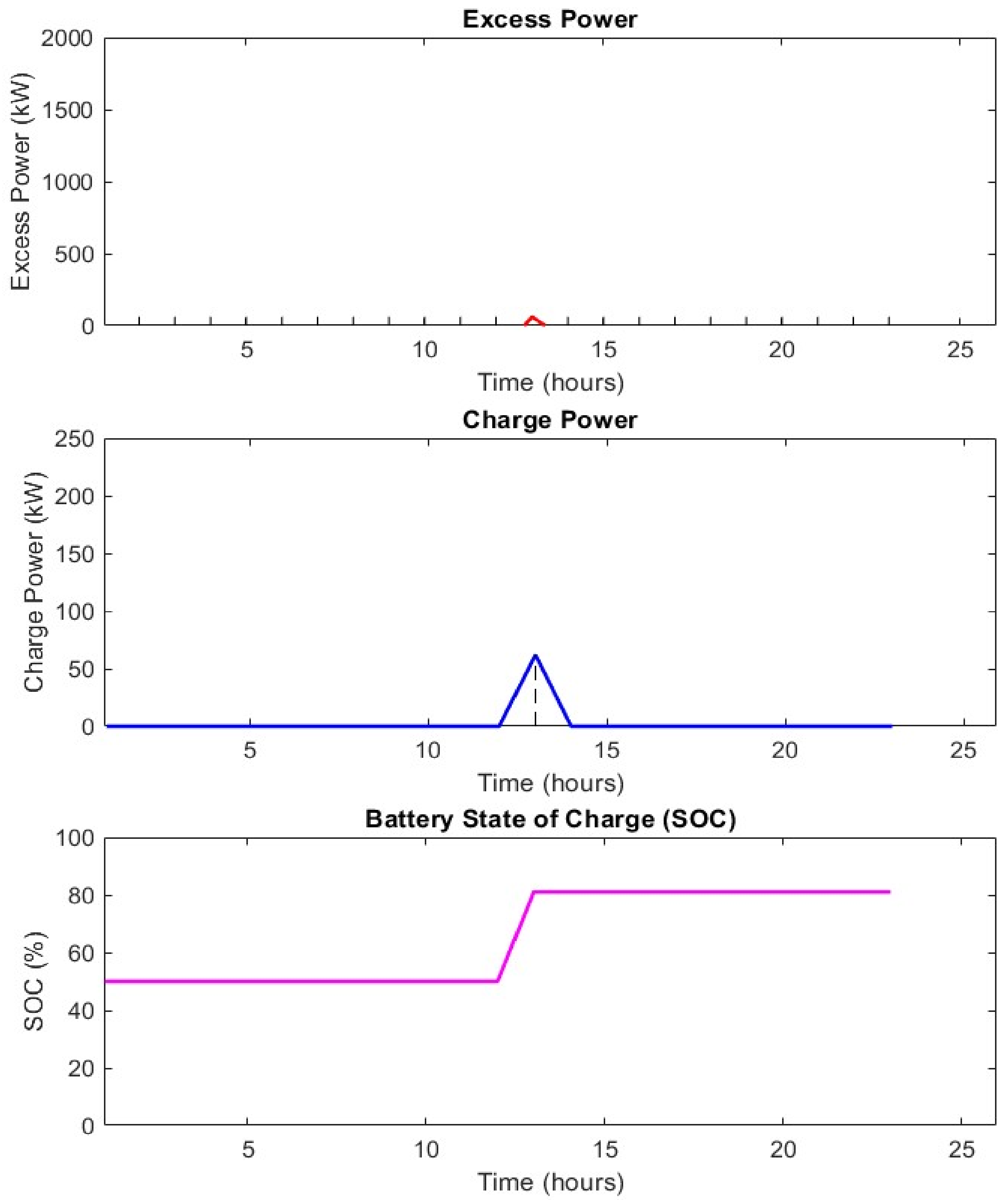


Figure 6.35 Dynamics of Excess Power, Charging Patterns, and SOC in Fall

6.4.3.2 Results Obtained AMPC

- Winter

  The operational dynamics on a winter day, as depicted in Figure 6.36, highlight the role of solar, wind, CHP, and grid power integration in primary control operations. At this level, real-time data is used to redistribute load demands between renewable and grid-based energy sources. To minimize grid dependency, AMPC system optimizes energy allocation for efficient resource utilization.

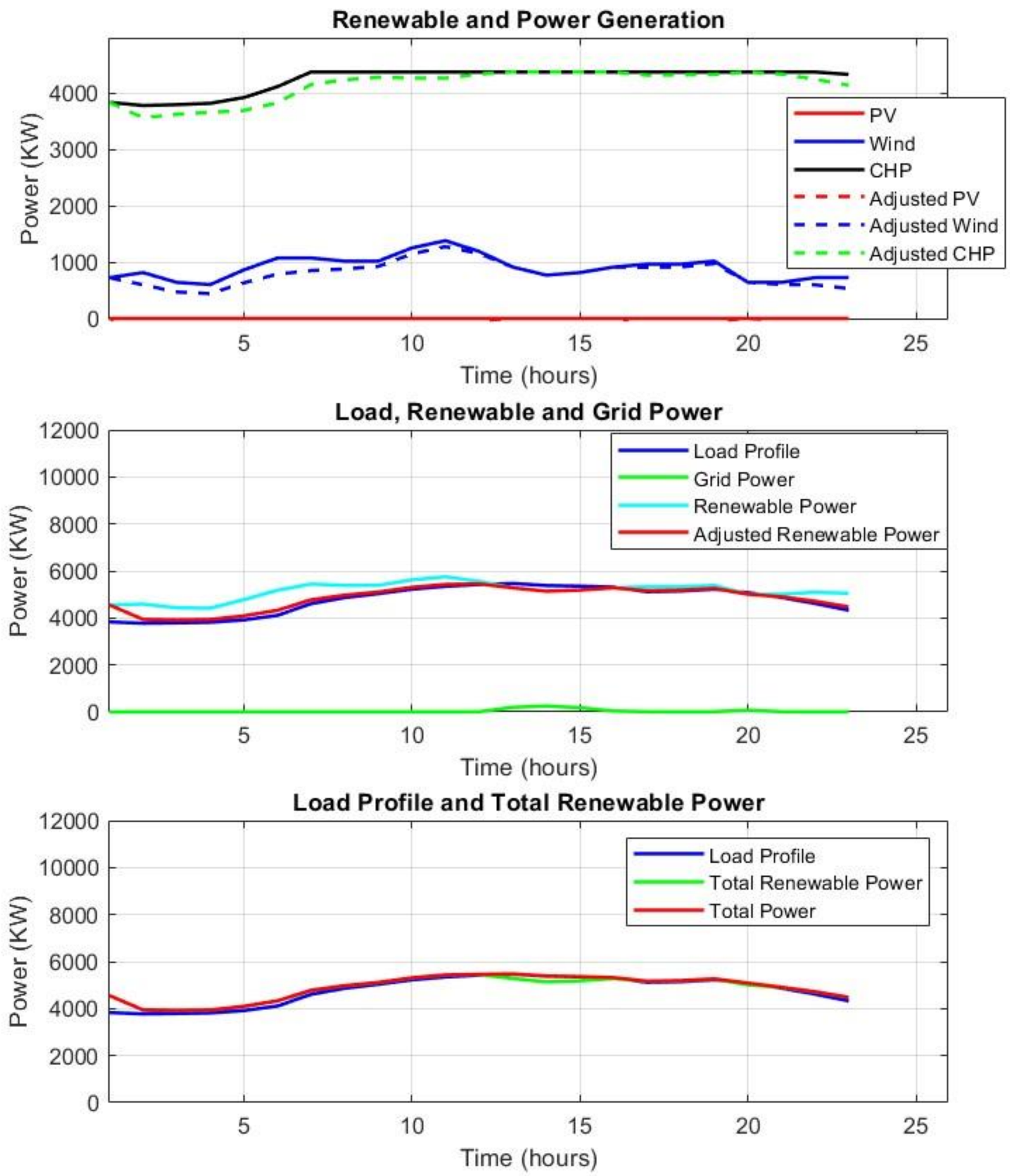


Figure 6.36 Load Profiles: Renewable vs. Grid Power Over 24 Hours in Winter

Figure 6.37 focuses on the management of excess power, battery charging, and state of charge (SOC) adjustments within the microgrid system. It illustrates how the control system effectively manages battery applications to ensure stability and optimize grid power usage. The excess power recorded, particularly during the day, results from the wind turbines (WT) generating more energy than the load demand, allowing for battery charging.

In winter, when solar energy generation is absent, the excess power primarily stems from favorable wind conditions. At night, the graph indicates excess power due to reduced overall energy consumption, which the system strategically manages. The control system anticipates low demand periods, ensuring that the batteries are sufficiently charged during the day for use at night. The alternating charge and discharge cycles of the batteries, as shown in the graph, play a crucial role in maintaining system stability.

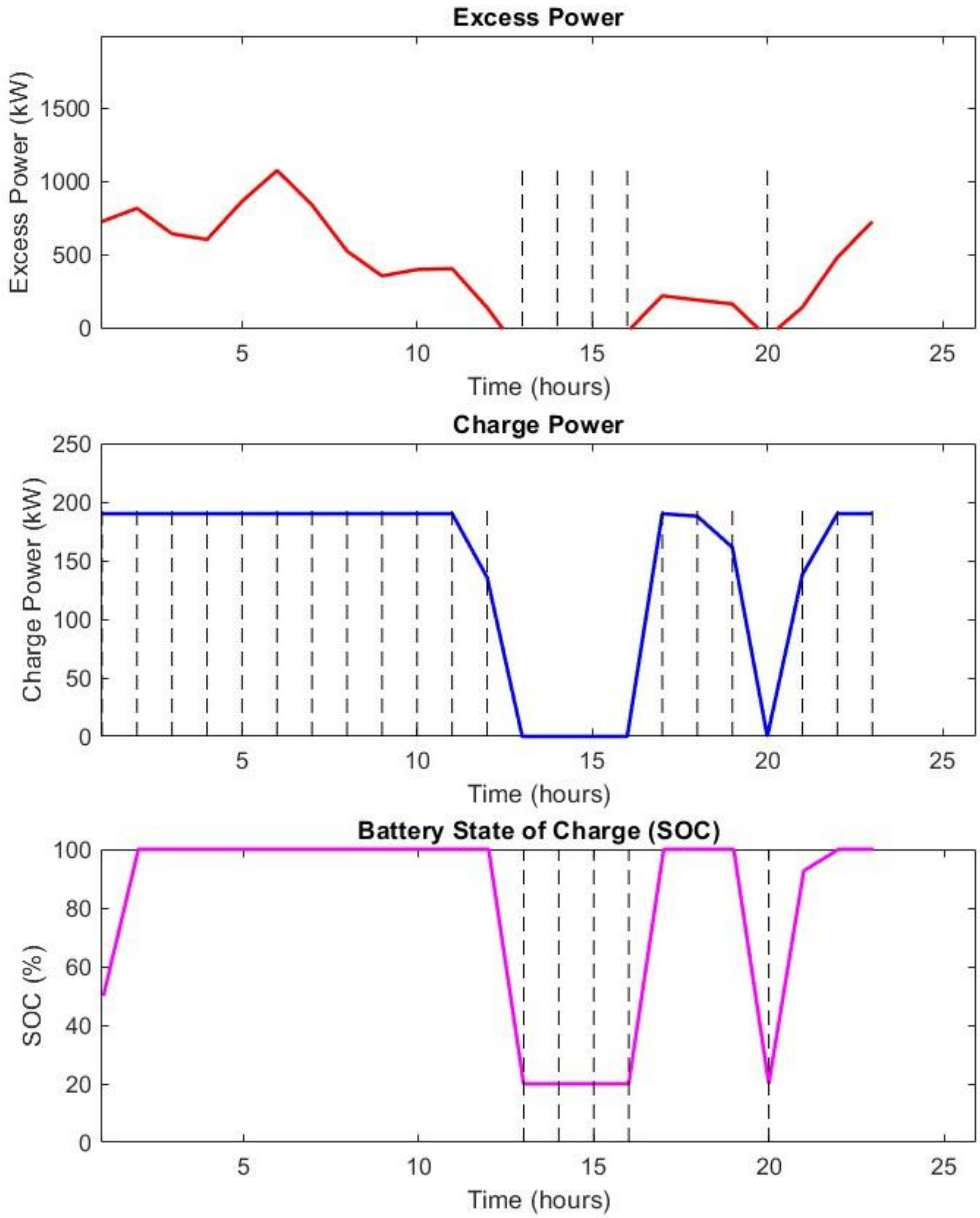


Figure 6.37 Dynamics of Excess Power, Charging Patterns, and SOC in Winter

- Spring

  During the spring season, renewable energy generation tracks below the load profile, so further dependence on grid electricity is increased at these early hours and peak periods. Under varying conditions, the primary control of the system allows for the combination of outputs from solar, wind, and CHP sources. As a result, grid independence is increased with the availability of renewable resources and load sharing management is enhanced by AMPC as it relates to the loads as illustrated by Figure 6.38.

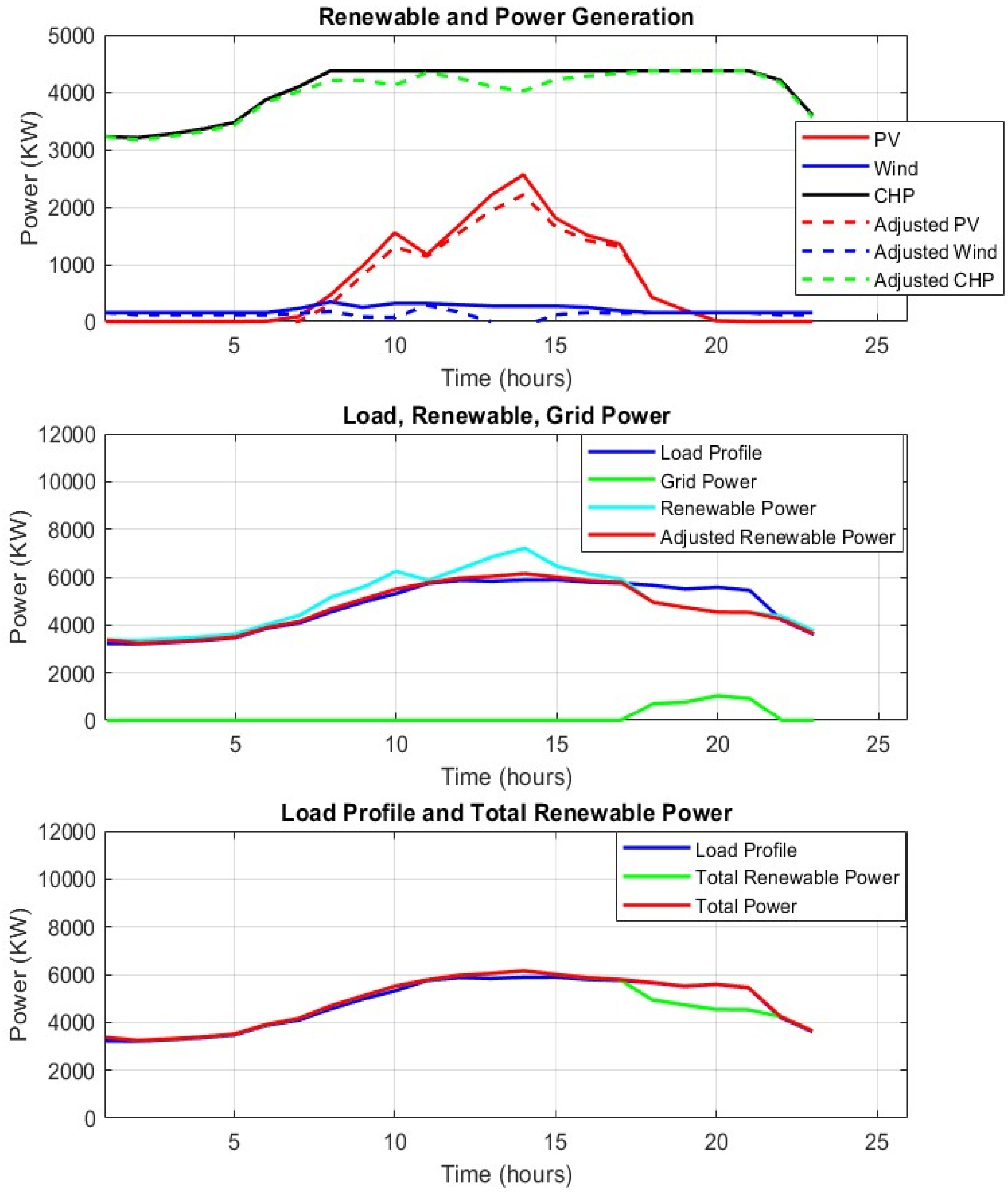


Figure 6.38 Load Profiles: Renewable vs. Grid Power Over 24 Hours in Spring

Figure 6.39: shifts focus to the battery management system during the spring season. It illustrates that excess power typically occurs around midday, leading to increased

battery charging from solar power, as shown in the middle graph. However, due to the generally lower wind speeds in spring, wind turbines contribute less to the power generation, limiting the overall renewable energy supply. The battery state of charge (SOC) increases significantly, indicating that the secondary controller prioritizes renewable energy for charging. During the night, when solar power is not available, the batteries supply energy to meet the load demand, ensuring a reliable energy supply throughout the day and night. This integrated management approach enhances the system's resilience and reduces dependency on the utility grid.

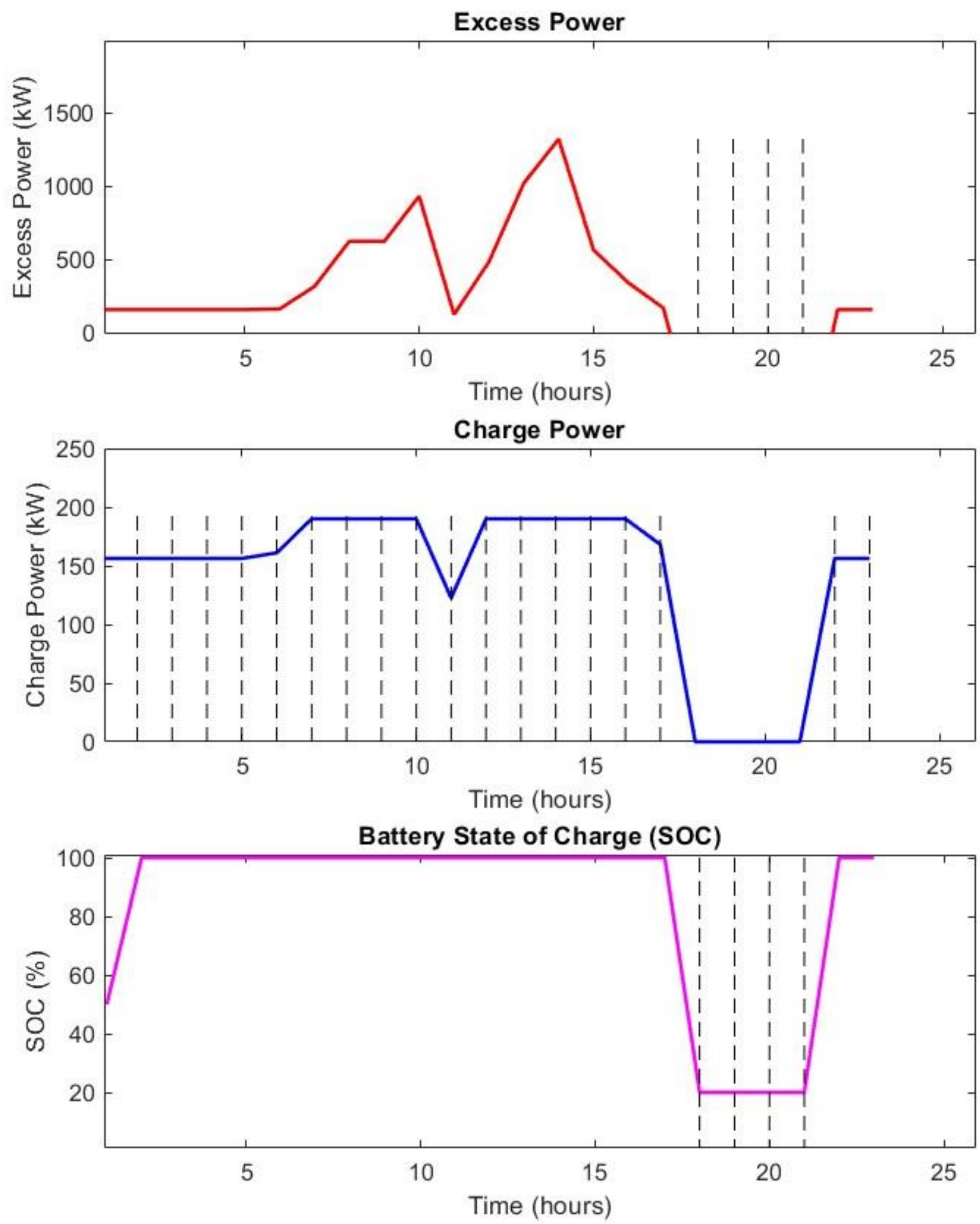


Figure 6.39 Dynamics of Excess Power, Charging Patterns, and SOC in Spring

- Summer

  As depicted in Figure 6.40, during the summer months, solar power generation reaches its peak, significantly reducing reliance on grid power, particularly during daylight hours. The tertiary control system demonstrates a high level of autonomy by effectively managing surplus energy, either by storing it or directing it to non-critical loads, optimizing overall system efficiency.

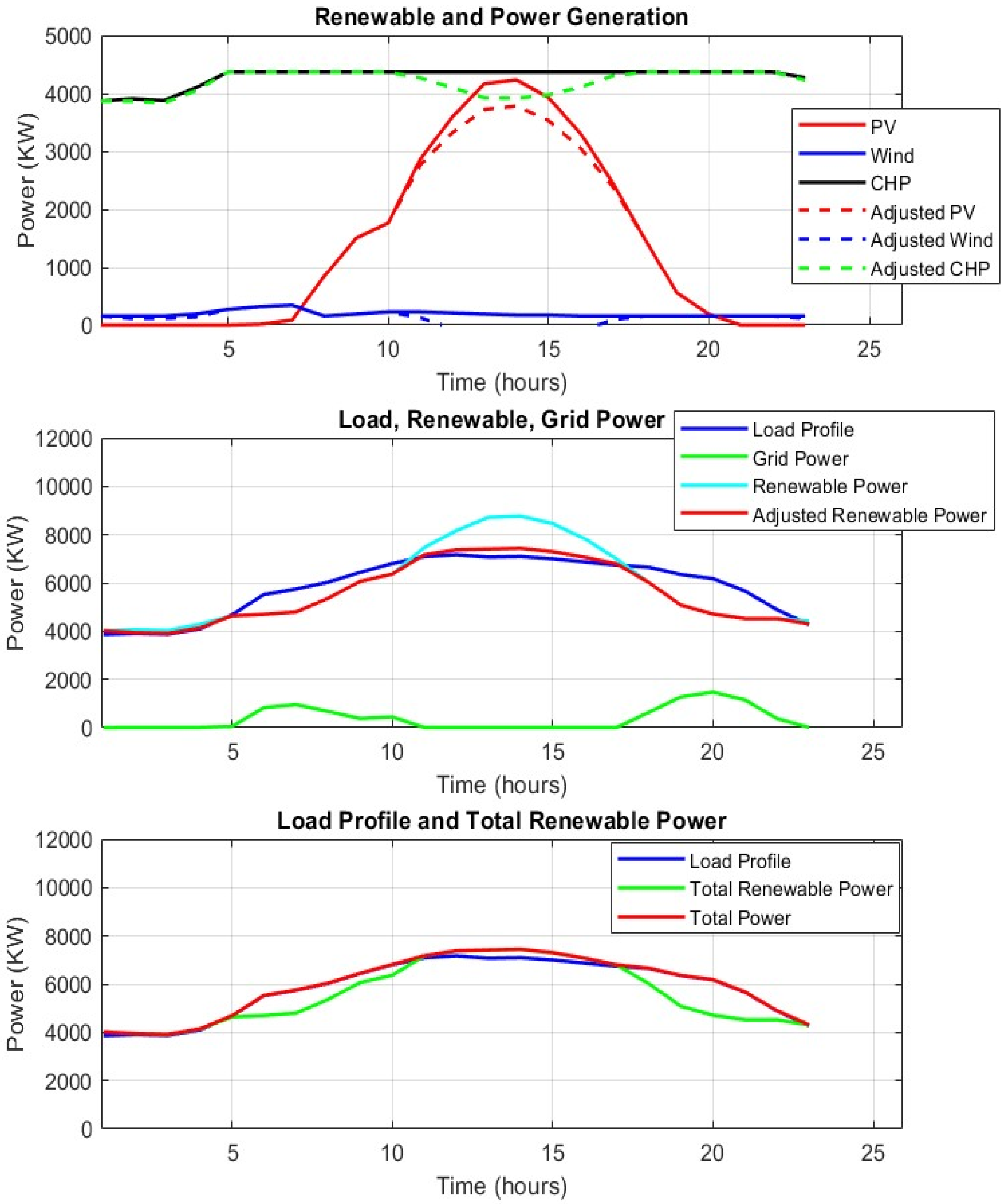


Figure 6.40 Load Profiles: Renewable vs. Grid Power Over 24 Hours in Summer

As illustrated in Figure 6.41, the energy management system operates effectively during summer, characterized by lower wind speeds, resulting in a heavier reliance on solar power during the day. The battery supplies power to the load between 5 AM and 10 AM, when solar energy is limited. Once solar generation becomes available, the battery begins charging. However, from 4 PM onwards, the battery starts supplying the load again until 11 PM. The graph indicates periods of excess power during peak solar generation hours, with a portion of this excess energy directed to charging the battery, as reflected in the charge power graph. The state of charge (SOC) graph demonstrates that battery storage is managed to ensure energy stability, showcasing control actions that maintain stability following peak charging periods.

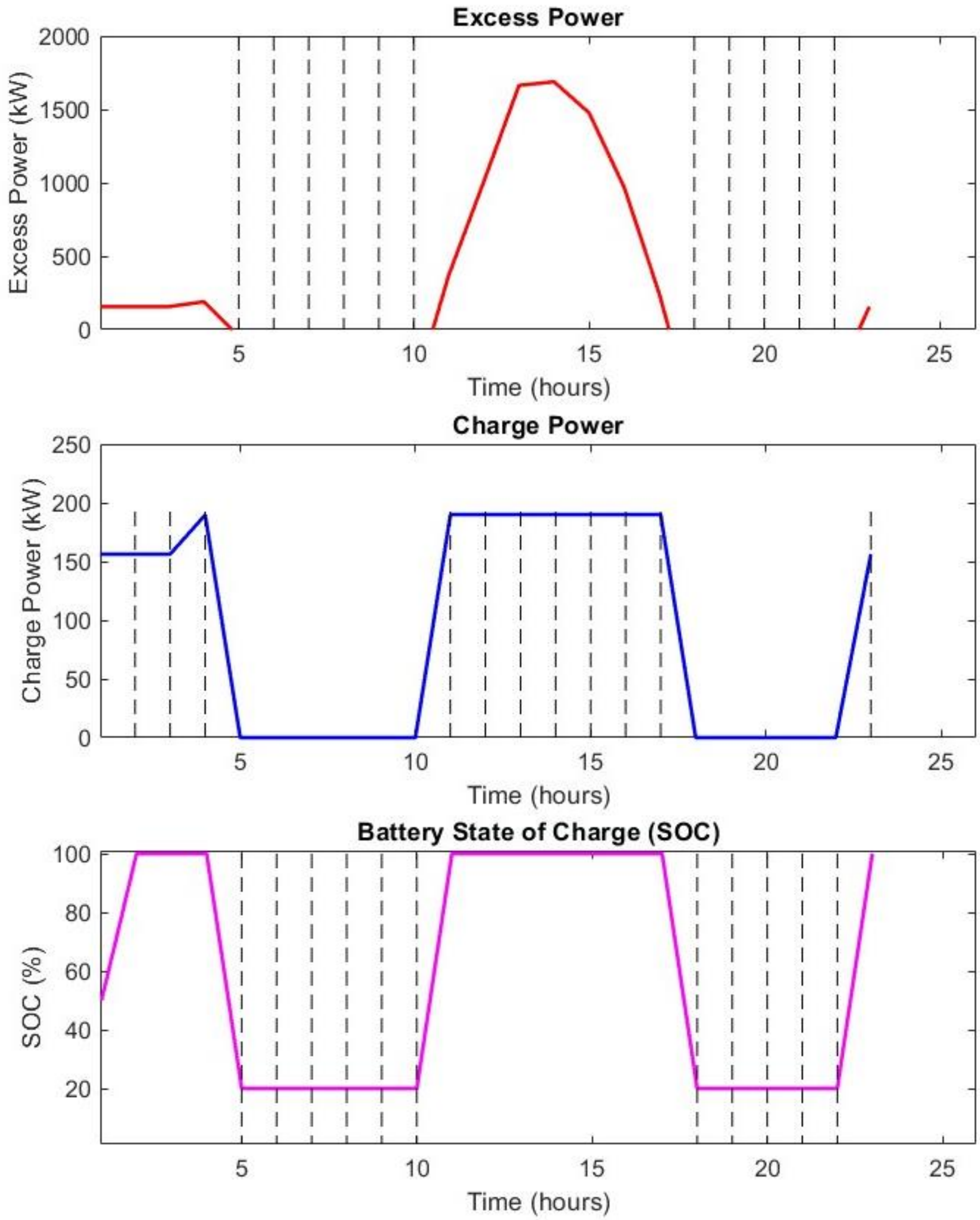


Figure 6.41. Dynamics of Excess Power, Charging Patterns, and SOC in Summer

- Fall

  Figure 6.42 illustrates the interaction between renewable energy generation, load demand, and grid support during the fall season. The output of wind and combined heat and power (CHP) systems is consistent, primarily during daylight hours, contributing to the management of base load. During the fall season, cloud cover typically reduces solar energy to a significant degree at midday, aligned with the sun's zenith. However, overall solar energy contributions are periodically reduced by clouds. To ensure energy supply continuity even when direct sunlight is intermittently obscured, dynamic control systems are used to adjust solar output. As a result of these fluctuations, storage systems are essential for stabilizing the grid and maintaining a consistent power supply by absorbing excess energy and releasing it as required.

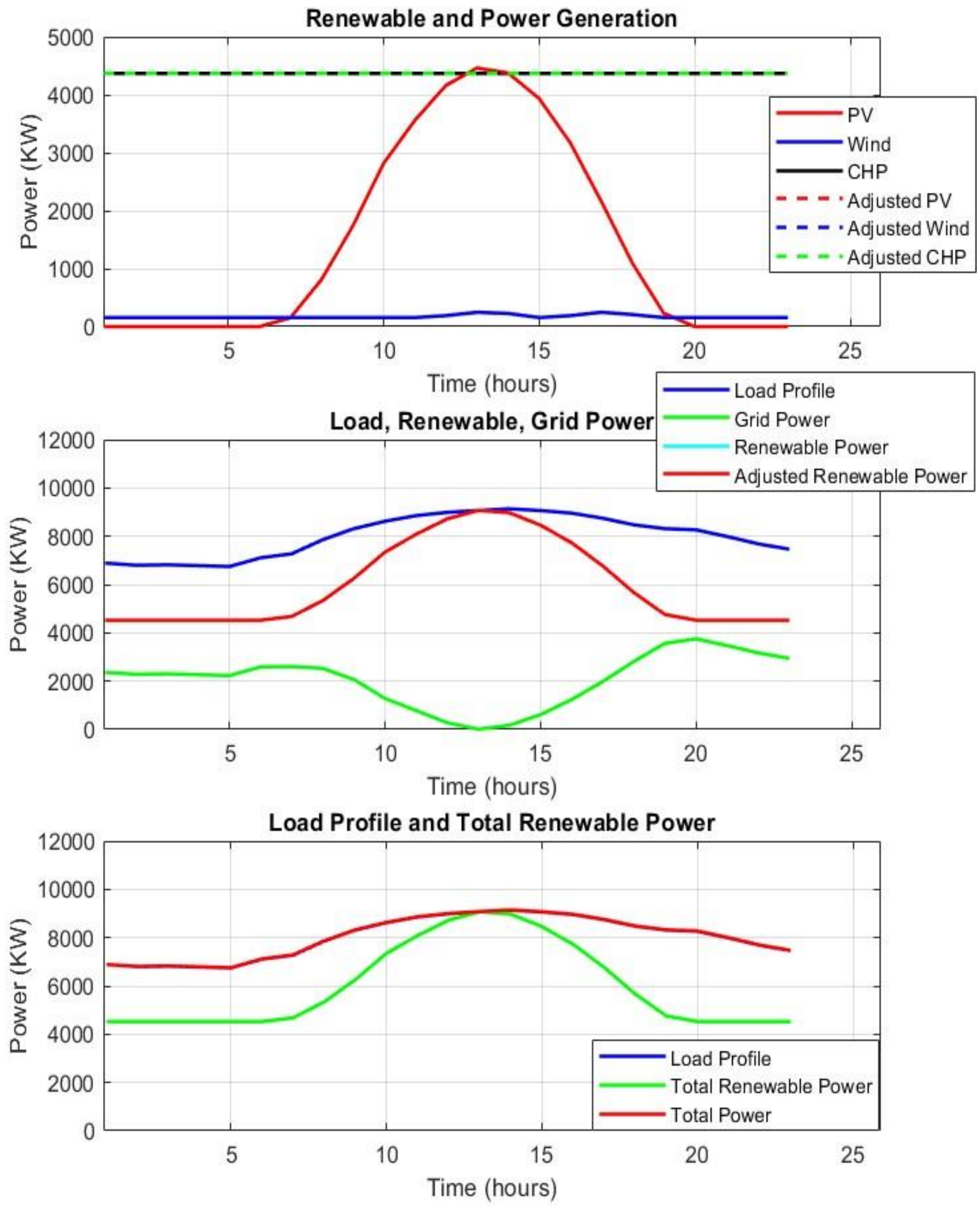


Figure 6.42 Load Profiles: Renewable vs. Grid Power Over 24 Hours in Fall

Energy storage dynamics are depicted in Figure 6.43 depicts the dynamics of renewable energy generation and power management within the microgrid system during a specific time frame. The top graph illustrates the generation from photovoltaic (PV) panels and the Combined Heat and Power (CHP) system, which operate efficiently during peak hours. However, despite the solar power generation, the load profile exceeds the available power during certain hours, resulting in no excess energy to charge the battery.

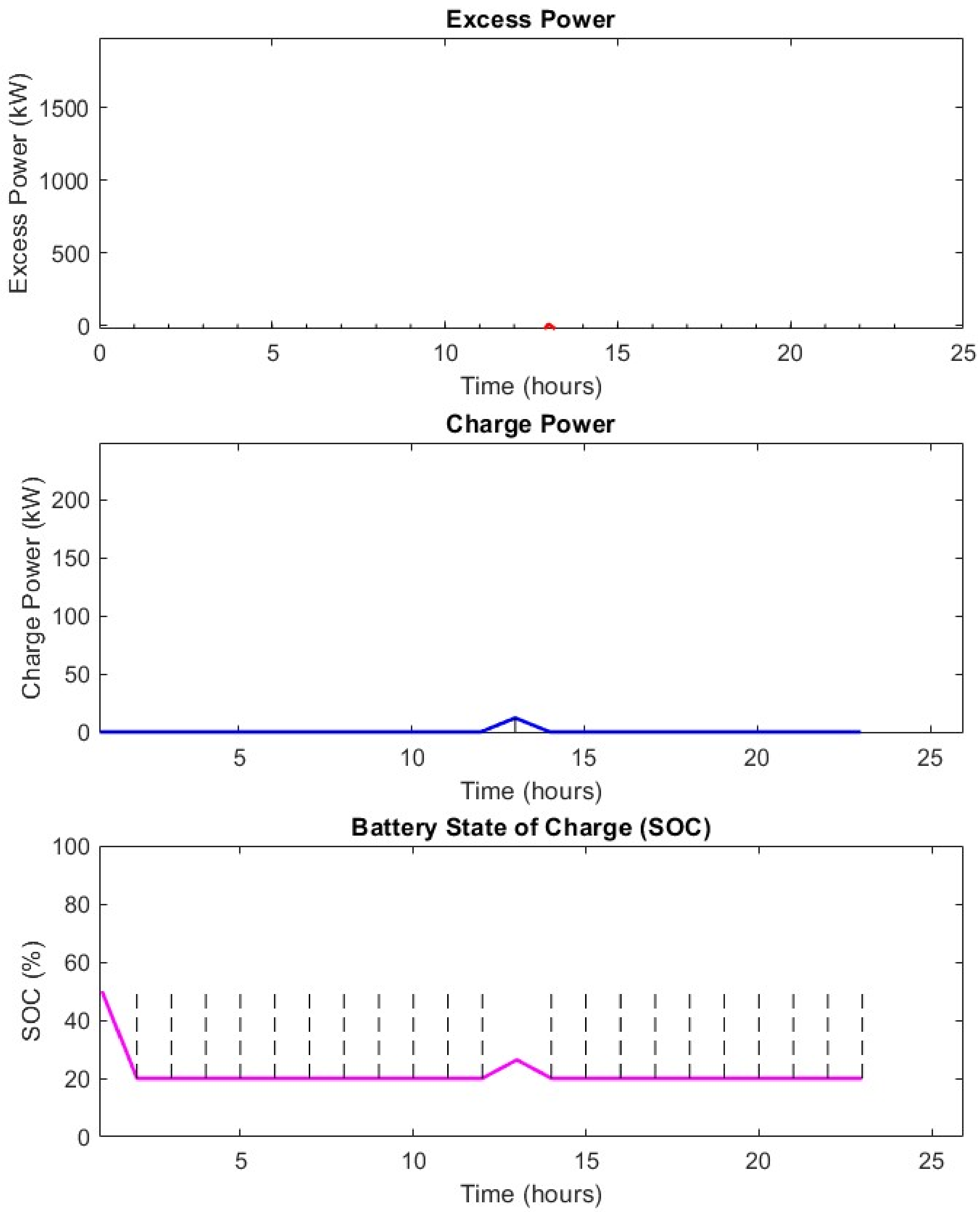


Figure 6.43. Dynamics of Excess Power, Charging Patterns, and SOC in Fall

- AMPC vs. Basic MPC Performance

  The results obtained from the analysis of basic MPC and Adaptive MPC indicate that AMPC outperforms basic MPC in effectively meeting load demand from various energy sources. Throughout the day, AMPC demonstrates superior capability in discharging the energy storage system (ESS) to supply power when needed. Additionally, it efficiently calls on utility support during periods of insufficient renewable generation. This adaptability ensures a more reliable energy management process, ultimately enhancing the overall performance of the microgrid.

- Seasonal Adaptation and Efficiency in Renewable Energy Management

  During the Winter season, solar energy is almost non-existence, thus the energy intake is mainly from wind power and support from the grid. Battery storage is also used to guarantee reliability of the energy supply and meet peak load demands even when wind generation is inadequate. Spring has better sunlight efficiency, which reduces the use of the grid system. The energy system enhances its operation by charging the batteries during the high solar production to ensure the effective utilization of energy when the solar generation output is low.

In summer season, solar energy is at its finest and is sufficient to meet the load demand the entire day. The surplus energy is used to charge the battery, in order for the system to be ready for instances with low generation. This season proved that microgrid can operate almost solely off the renewables and can do so without needing to import power from the grid. Fall has good solar power generation which in some extent can decrease the reliance on the grid. Solar and wind generation resources are combined with the optimum utilization of battery storage systems to guarantee that the energy needs are adequately satisfied when there is less sunlight. The system very effectively switches from the solar to the wind power in the evening using the stored energy to provide a constant power output.

This shows that the year-round approach to battery storage management can address the variability of renewable energy generation that is typical for different seasons. It helps reduce grid reliance in the time of high renewables output in the Spring and Summer and offset lower outputs in the Fall and Winter. These adaptive control systems show their potential in accommodating the fluctuations in energy production and consumption throughout the year without affecting the stability and performance of the system as regards the integration of renewable and grid resources.

6.4.4 Seasonal Energy Cost Analysis

- Grid Energy Costs Without Microgrid

  Energy price varies considerably by season and the fall season reaches a top of $21,600, which is attributed to higher consumption or more expensive utility costs. Among seasons, spring has the lowest at $13824. Cost figures for costs associated with winter and spring are almost the same, with winter costs at $14544 and summer rising to $15840, as a result of refrigerator and air conditioning loads. These changes are displayed in Figure 6.44, while also indicating the volatility of grid related costs.

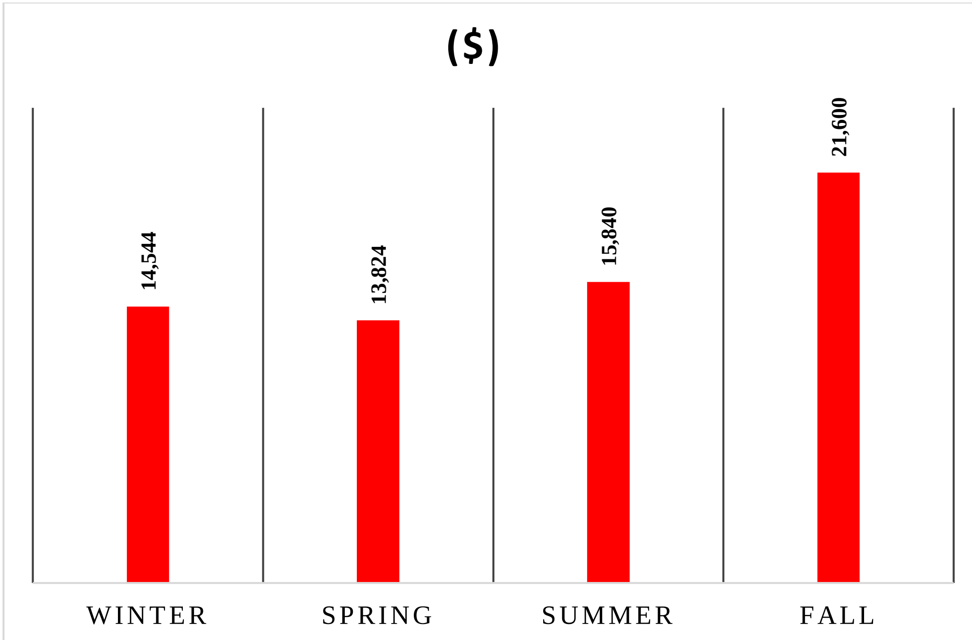


Figure 6.45 Grid Energy Without Microgrid

- Seasonal Costs After Microgrid

  Microgrid implementation balances energy costs across seasons, with winter and fall nearing $11,000 due to higher demand, while spring and summer are lower, around $9,000, benefiting from solar efficiency. Figure 6.46 highlights this trend, showing stable costs despite varying seasonal demands. The microgrid effectively manages energy consumption throughout the day.

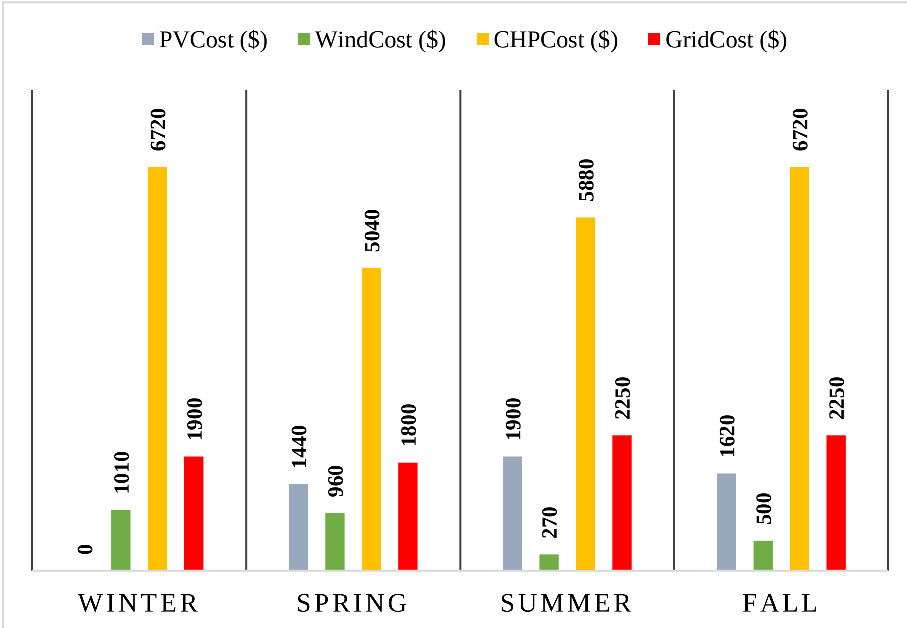


Figure 6.46 Post-Microgrid Seasonal Costs

- Total Microgrid Costs Per Season

  The microgrid ensures a balanced distribution of energy costs across seasons. In winter and Fall are connected with highest cost of $11000. Spring and summer are lower, with spring being the least expensive at just over $9,000. Figure 6.47 illustrates this stability, highlighting the microgrid's ability to manage seasonal variations effectively. This approach ensures that there are no fluctuations in energy costs during the time of the day.

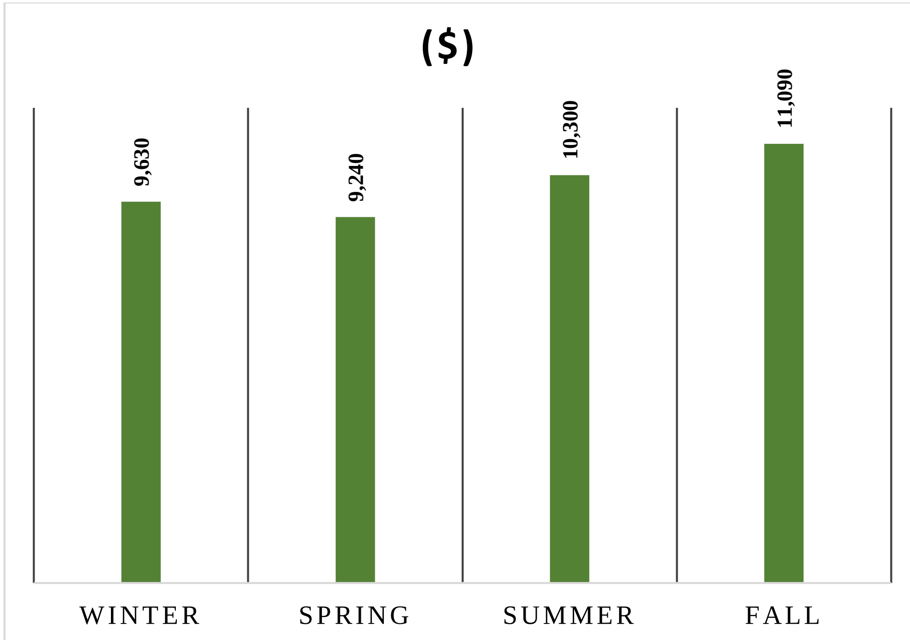


Figure 6.48 Total Seasonal Energy Cost with microgrid

- Seasonal Cost Savings with Microgrid

  The microgrid provides significant energy cost savings, varying across seasons. Fall achieves the highest savings, exceeding $10,000, due to reduced reliance on traditional grid power. Winter, spring, and summer see more moderate savings, around $4,000 to $6,000. Figure 6.49 highlights these seasonal savings, showcasing the microgrid's ability to align energy generation with demand. This trend demonstrates its potential to reduce costs throughout the year.

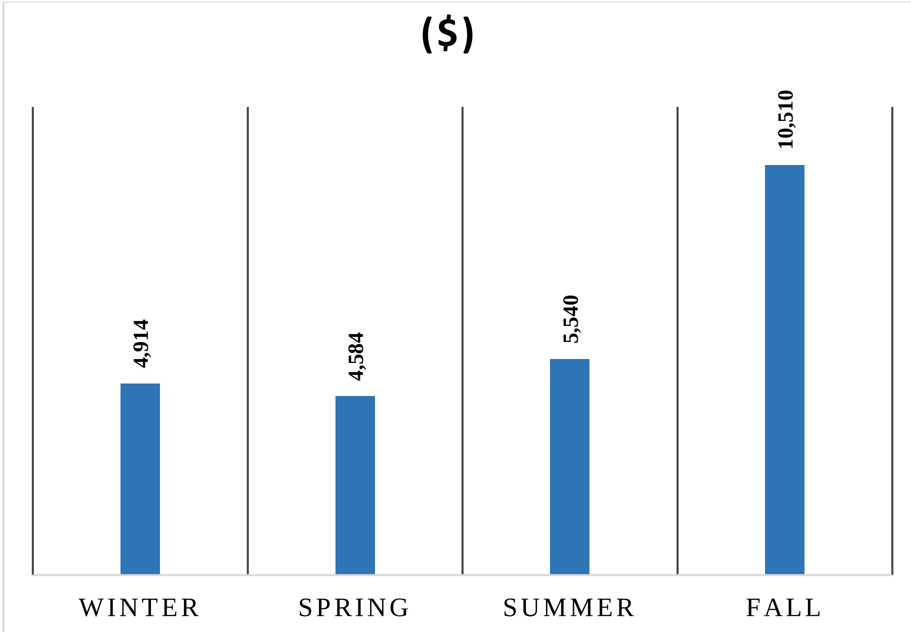


Figure 6.49 Seasonal savings

CHAPTER SEVEN

CONCLUSION AND FUTURE WORK

7.1 Conclusions

The present work focuses on the analysis and control of the hybrid microgrid systems with an emphasis on university campus energy systems. The literature survey carried out on campus microgrid systems indicated the increasing significance of microgrid system usage as a means of enhancing sustainability, diminishing fossil fuels, and increasing energy security on campuses. Nevertheless, some obstacles still persist, especially those associated with the variability of renewable sources and the challenges in the design of control systems. It was observed that PID and rule-based control systems had basic difficulties managing systems requiring action in a dynamic and any complex environment. Hence, the need for more advanced strategies became evident.

A HOMER simulation at Oakland University was used as a case study, showing the possible implementation of hybrid microgrids for campus use. It was revealed that the multi-objective optimization of distributed energy resources such as PV, wind turbines, CHP, and battery storage systems lead to cost-effective energy reliability solutions. In addition, simulations carried out within HOMER provided an answer on how one can effectively design and optimally operate green energy systems with a focus on their costs, efficiency, and environmental impacts.

Research into Modified Firefly Algorithm (MFA) to optimize the hybrid microgrids has made it clear that the algorithm is far better than the conventional Firefly Algorithm.

The concept of dynamic modifications applied in MFA was applied to the multi-objective optimization in such a way that further improvement would be achievable on NPC, LCOE and GHG reduction. These improvements show that GFS needs to be more robust and efficient in the management of its energy system.

The multi-level control architecture implemented with Adaptive Model Predictive Control (MPC) helped to show that the dynamic and uncertain characteristics of the microgrid would not be a challenge in control of the hybrid microgrids. The adaptive features of the MPC embedded in the MPC to take care of time-sensitive changes positively contributed to control of variations in renewable energy sources and load to protect the system from instability while optimizing power distribution.

7.2 Contributions

This investigation has largely advanced the scholarship on hybrid microgrid control and optimization as well as on renewable energy management. The work is presented in theoretical, applicative, and algorithmic and control conceptualizations of optimizations, which in aggregate enhance the limits of current microgrid research. The following list emerges as key contributions:

- Systematic literature review of campus microgrid systems provided a thorough review of existing information on management of campus microgrids.
- Utilization of HOMER for microgrid conceptualization showed the practical application of hybrid renewable energy systems specified for campus needs, simulated by HOMER, and regarding the most effective way of a system's configuration and its operation.

- Multi-objective optimization supports by Modified Firefly Algorithm created a dynamic, improved modification of the Firefly Algorithm MFA, which increased the speed and accuracy in solving complex multivariable objectives within microgrid energy system management.
- Advanced multi-level control of distributed resources via adaptive MPC presented an efficient and robust multilevel control system that combines Adaptive MPC for advanced management of distributed energy resources in a hybrid microgrid, facilitating easier and more effective system control.

7.3 Future Work

Although this research has addressed key challenges in hybrid microgrid control and optimization, several opportunities for future exploration remain. These areas will help extend the findings of this dissertation into new domains and improve the applicability of the developed frameworks. The following directions are suggested for future work:

- Enhanced Predictive Modeling for Renewable Energy Resources.

  Future work could focus on improving forecasting models for renewable energy generation (e.g., solar, wind) by integrating machine learning algorithms to enhance the real-time predictive capabilities of Adaptive MPC.
- Integration of Advanced Energy Storage Systems.

  Research should explore advanced energy storage solutions, such as solid-state batteries or hydrogen storage systems, to complement hybrid microgrids and optimize the charge-discharge cycles of energy storage systems.

- Scalability of the Control Framework.

  Investigating the scalability of the proposed multi-level control framework for larger microgrid systems (e.g., city or regional microgrids) will be essential to evaluate its effectiveness in larger-scale implementations.

- Real-World Pilot Implementations.

  Future research could focus on real-world applications of the developed control framework, expanding beyond university campuses to industrial microgrids, rural electrification, and smart city projects to validate and refine the proposed strategies.

APPENDIX

Table A-1 Details of ESS classification [150]

Ref.	Category	Types/Model	Operation	Modes	Advantages	Disadvantages
[151]	Electrochemical	Sodium sulphur, lead acid, nickel-cadium, and lithium-ion	Energy is converted from chemical to electrical energy in active materials	Batteries that are conventionally rechargeable, as well as batteries that are flow rechargeable	Storage devices come in a variety of sizes and require minimal maintenance	Chemical reactions reduce battery life and energy
[152, 153]	Thermal	Solid, liquid with filler, or pure liquid (e.g., stone, molten salt, water).	Heat or ice is used to store energy	High-temperature and low-temperature	The technology provides secure, eco-friendly, high-density energy.	Low life expectancy
[154-158]	Hybrid	The battery can connect to an SC, an SMES, an FC, an SC, and an RFB.	Multi-ESS integration	Combines high power and energy storage to enhance stability, reliability, and reduce power quality issues.	Improves system efficiency and extends battery life	High costs
[159, 160]	Chemical	Hydrogen, diesel, propane, ethanol, and liquefied petroleum gas	Electricity can be directly generated	Chemical bonds within atoms and molecules are responsible for storing energy	Abundant raw materials lower costs by storing large energy amounts long-term.	Developing this technology requires a high level of efficiency

Table A-1 Details of ESS classification (continued)

Ref.	Category	Types/Model	Operation	Modes	Advantages	Disadvantages
[48, 161]	Mechanical	Compressed air, flywheel, and pumped hydro storage	Assists mechanical work by delivering the stored power	Kinetic energy potential energy, forced spring, and pressurized gas	Utilizes flexible methods of converting and storing energy	Geologically, it is costly to implement, has a negative environmental impact, and is not economically feasible

Table A-2 Microgrid systems with resource, and solver

Ref.	Campus Name	Resources	Methodology	Load Types	Contribution	Results
[70]	University of Coimbra, Portugal	PV, ESS	Control algorithms, IoT	HVAC loads	Improved building microgrid flexibility	Increased energy efficiency
[162]	National University of Sciences and Technology, Pakistan	PV plant, ESS, EVs, DG	MILP, ant colony optimization, LP	Campus load	Reduction of operational cost, analysis of DGs, and optimally scheduled ESS	ESS minimizes operational costs from USD 798,60 to USD 756,3850
[163]	Guangdong University of Technology, China	-	Self-crossover genetic algorithm, DSM optimization model	Controllable and non-controllable loads, micro-market operations	DSM scheme for microgrids with sub-decision makers	Reduction in electricity cost
[164]	Cochin University of Science and Technology, India	PV, WT, and biomass.	Static and time domain simulations, eigenvalue analysis	-	Eigenvalue analysis confirmed small signal stability of a renewable microgrid for load increases of 1.26 p.u in grid mode and 1.25 p.u off-grid...	RESs meet most power demand with minimal loss, maintaining stability for large load increases in grid and off-grid modes.

Table: Table A-2 Microgrid systems with resource, and solver (continued)

Ref.	Campus Name	Resources	Methodology	Load Types	Contribution	Results
[165]	NFC Institute of Engineering and Technology, Pakistan	PV, ESS, and Evs	LP	Campus load	Integration of PV system, ESS, and EV in a university campus, optimal Energy Management System (EMS)	EMS reduces energy costs by 45%, with EV cutting costs by 45.58% as a source and 19.33% as a load. Power impact analyzed.
[166]	University in Southern Java Island, Indonesia	PV power generation plant	HOMER Pro software,	Campus load	Feasibility analysis of solar energy system, techno-economic analysis, potential contributions, and applicability	Simulation studies for identifying cost-effective configurations
[167]	University Campus in Brazil	PV and BESS	Simulated annealing algorithm	Campus load	EMS coordination, optimal operation of battery system, reduction in energy consumption costs	Minimize campus energy consumption and costs
[168]	Clemson University-Main Campus, UAS	PV and BESS	Emulated virtual inertia, coordination controller	Campus load	Design and operation of a microgrid, seamless transition between grid-connected and islanded modes, IEEE Std 1547.4 compliance	Emulation of virtual inertia for resiliency
[169]	Faculty of Technical Sciences in Novi Sad, Serbia	PV, WT, EV, BESS, biogas micro-turbine	Microcontroller, interface, consumers	-	Application of distributed energy resources, stable island mode specifications, and techno-economic and environmental analysis.	Microgrid proposal includes technical analysis for stable operation, focusing on energy production, costs, and avoided emissions.

Table: Table A-2 Microgrid systems with resource, and solver (continued)

Ref.	Campus Name	Resources	Methodology	Load Types	Contribution	Results
[170]	U.E.T, Taxila, Pakistan	Diesel Generator, and ESS	MILP, MATLAB simulations	Campus load	Reduction of operational cost, increased self-consumption from green DGs, reduction in grid electricity cost	Proposed EMS model for institutional microgrid, reductions in grid electricity cost
[1]	Oakland University, USA	Solar PV, ESS, CHP, and WT	HOMER Pro software	Campus load	Optimal planning and design of hybrid renewable energy systems, scalable and flexible MG configurations	The guide minimizes NPC and LCOE, offering a cost-effective plan for sustainable hybrid energy in microgrids.
[171]	North China Electric Power University, Beijing, China	PV, WT, CHP, ESS, and EVs	MTPSO	Campus load	Optimal scheduling of power sources Consideration of demand response	The model outperforms PSO in hybrid microgrids, with simulations confirming effectiveness.
[172]	University of California, San Diego, USA	PV and full cell	Economic optimization	Campus load	State-of-the-art microgrid development, 42 MW microgrid, 92% self-generation of annual electricity load	Microgrid PV panels save USD 800,000 monthly, enhance grid infrastructure, and boost self-generation for electricity.
[73]	Princeton University, UAS	Gas turbine, solar, CHP, and ESS	Digital controls	Campus load	Multiple fuel sources, diverse power assets, CHP production.	Microgrid cut emissions, boosted reliability, and earned revenue.

Table: Table A-2 Microgrid systems with resource, and solver (continued)

Ref.	Campus Name	Resources	Methodology	Load Types	Contribution	Results
[72]	University of California, San Diego, USA	Gas turbines, Steam turbine, PV, molten carbonate FC, thermal energy storage bank	VPower analysis, SCADA system	Campus load	85% of electricity, 95% of heating and cooling needs, 75% fewer criteria pollutants, 30% federal investment tax credit	Improved environmental efficiency, significant coverage of campus energy demands, financial incentives for sustainability
[173]	University of Genoa, Italy		Model Productive Control (MPC)	Campus load	Increased overall energy efficiency, lower primary energy consumption, environmental and economic sustainability	Reducing emissions, primary energy use, and costs
[174]	Chiang Mai Rajabhat University, Thailand	PV, DG, and biomass gasifier	-	Smart community	Hybrid PV-DC microgrid system design and evaluation, application of DC loads	A practical hybrid PV-DC microgrid system was developed, including a PV-AC microgrid, diesel generator, biomass gasifier, and local grid connection.
[175]	Hangzhou Dianzi University, China	PV, DG, fuel cells, and BESS unit	-	Campus load	The primary power source includes PV panels, a diesel generator, and fuel cells, integrated with a capacitor bank and battery storage.	The first microgrid with 50% PV used 728 solar panels across 946 m², staying stable with intermittent power sources.

Table: Table A-2 Microgrid systems with resource, and solver (continued)

Ref.	Campus Name	Resources	Methodology	Load Types	Contribution	Results
[176]	Technical University of Denmark	PV, WT, and vanadium-based battery system	Experimental tests for static and dynamic stability analysis	Laboratory scale load	The implementation and testing of various control strategies for the combined system followed the development of appropriate models for the SYSLAB microgrid	Test results included static and dynamic stability, disturbance impacts, DER modeling parameters, and model creation for the SYSLAB microgrid.
[177]	Nigerian University	PV panels, inverter, grid system, DG set	HOMER Pro software	University community load	A microgrid system was designed and sized to tackle power challenges within the Nigerian national grid	PV panels can generate 88% of the campus's annual energy, reducing both the electricity bill and CO2 emissions by 88%.

Table A-3 Microgrid components configuration

Component	Manufacturer	Specifications	Required Quantity
Wind Turbine	Composite	Rated power: 1.5 MW, router diameter: 90 m, speed class: III, hup height: 30 m, lifetime = 20 years	1
Photovoltaic	SunPower	Panel rated power: 335 W, average efficiency: 21% Model: X21-335-BLK	1791 panels
CHP (J624 H01)	Jenbacher	CHP rated power: 4369 KW, f: 60 Hz, V: 4160 V, fuel: natural gas	1 unit
Battery	Idealized Homer model	Nominal voltage: 600 Nominal capacity (KWh): 1×10^3 Nominal capacity (Ah): 1.67×10^3 Roundtrip efficiency: 90% Maximum charge current (A): 1.6×10^3 Maximum discharge current (A): 5×10^3	3 batteries

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