A Cost-Efficient Approach for EV Energy Management in a Microgrid

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Submitted in fulfillment of the requirements

for the degree of Master of Science

in Electrical and Computer Engineering

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April 2024

Abstract

This thesis introduces a particle swarm optimization (PSO)-based energy management system (EMS) integrated into a microgrid (MG) infrastructure for charging electric vehicles (EV). The primary objective of this study is to enhance the efficiency of integrating locally produced renewable energy, power from the grid, and battery energy storage systems (BESS) to achieve cost-effectiveness and optimize the usage of sustainable resources within a community context. The design of the MG incorporates several components, including wind turbines (WT), solar panels (PV), and EV charging stations. The demand and energy generation profiles are modeled and used as MG inputs for analyzing 16 different scenarios with four seasons. The results demonstrate the versatility and effectiveness of the PSO-based EMS in attaining a financially viable MG system that satisfies the hourly energy demand criteria. This study aims to thoroughly comprehend the influence of the optimized EMS on EV charging schedules and MG performance. The findings of this research provide valuable insights for the development of sustainable and economically feasible EMS in community settings. Overall, the use of PSO in the proposed EMS for EV charging and battery charging/discharging is based on electricity price. Additionally, the results show that the implementation of PSO-based optimization results in a cost reduction of 21% and 16% in winter, 17% and 8% in spring, 12% and 9% in autumn, 21% and 14% in summer with and without EV consideration, respectively. These findings highlight the effectiveness of the PSO optimization technique in efficiently adjusting to various energy demand patterns.

Keywords: Energy Management System, Electric Vehicle Charging, Microgrid, Particle Swarm Optimization, Proactive technique, Renewable Energy

Acknowledgments

I gratefully thank my supervisor, **Prof. Mehdi Bagheri**, for his tremendous efforts, useful advice, and significant guidance, all of which led to the thesis's successful completion. His intellectual expertise, insightful critique, and frequent aid have elevated the quality of my work and helped me improve my research skills. I would like to thank my co-supervisor, **Prof. Amin Zollanvari**, for his unwavering moral support as I prepared my thesis. He has been a huge help in bringing me to the finish line, providing instruction and support.

Finally, I want to genuinely thank my **parents** and **friends** for their consistent encouragement, assistance, and prayers during my academic career. I also want to express my sincere gratitude to Ayesha Rauf and Usama Asif who have supported me wholeheartedly throughout this trying road. Their encouragement and blessings have helped me achieve great success.

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List of Abbreviations

AC	Alternating Current
ADMM	Alternate Direction Method of Multipliers
BESS	Battery Energy Storage System
DC	Direct Current
DER	Distributed Energy Resource
DR	Demand Response
DG	Distributed Generation
EMS	Energy Management System
EV	Electric Vehicle
GHG	Greenhouse Gases
G2V	Grid to Vehicle
GHI	Global Horizontal Irradiance
HESS	Hybrid Energy Storage System
H2G	House to Grid
HOMER	Hybrid Optimization of Multiple Energy Resources
HAWT	Horizontal-axis Wind Turbines
HBMO	Honey Bee Mating Optimization
LD	Load Demand
MG	Microgrid
MILP	Mixed-Integer Linear Programming
PSO	Particle Swarm Optimization
PHEV	Plug-in Electric Vehicle
PV	Photovoltaic
PG	Power Generation
RES	Renewable Energy Source

RB-EMS	Rule-based – Energy Management System
SOC	State of Charge
USA	United States of America
V2G	Vehicle to Grid
VCS	Virus Colony Search
VAWT	Vertical-axis Wind Turbine
WT	Wind Turbine

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Chapter 1 - Introduction

The increasing number of smart grids has raised numerous obstacles in the preservation of power quality and consistency. Grid-connected energy management systems (EMS) has experienced significant growth in recent years as a result of increasing energy usage. The EMS developed by microgrid (MG) allows optimal scheduling of renewable energy sources (RESs), power storage, and charging for electric vehicles (EVs) to effectively manage the equilibrium between supply and demand while ensuring cost-effectiveness. There is a growing concern among urban populations regarding the escalating levels of atmospheric greenhouse gases (GHG) resulting from the rapid growth of urbanization and rising numbers of on-road vehicles. Developing a viable and enduring substitute for the transportation infrastructure is crucial to address this issue. Incorporating RESs into MGs presents a viable approach to address environmental concerns and provide a cost-effective EMS [1]. The common sources of electricity generation are fossil fuels, including oil, gas, and coal. The aforementioned technique clearly showed reliability and efficacy; nonetheless, it has significant limitations in addressing the challenges related to GHG emissions. An in-depth analysis of the worldwide electrical grid demonstrates that an important portion of the populace still lives in rural regions, encountering challenges in accessing dependable, reliable power or a consistent provision of electricity [2]. The transportation sector of any nation produces substantial quantities of GHG emissions, which exert an adverse influence on the Earth's climate. Fig. 1.1 illustrates representative statistics related to GHG emissions across multiple countries globally.

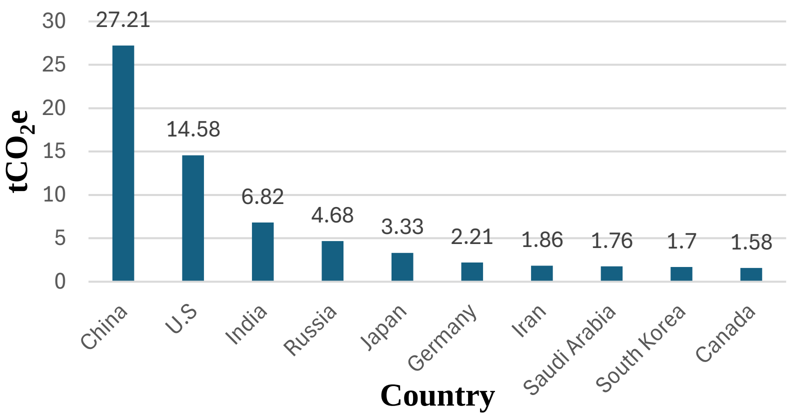

Figure 1. 1: Statistics representing GHG emissions across multiple countries, taken and modified from [3]

Global energy demand is projected to increase by 48% from 2012 to 2040 as reported by [4]. In 2012, there were 32.2 billion metric tons of carbon footprint caused by electricity, which is expected to climb to 43.2 billion metric tons by 2040 [4]. In addition, it is anticipated that conventional energy sources, including fossil fuel, coal, and gasoline, will experience significant consumption in the coming years [5]. Due to these factors, the subject of renewable energy generation and consumption has received significant focus, and these technologies have been extensively implemented worldwide [6]. When implemented and used correctly, renewable energy can reduce energy expenditures compared to conventional methods, which can have adverse environmental consequences. The construction of more effective EMS has been assisted by advancements in MGs and the spread of RESs [7]. The use of EVs is experiencing rapid growth. By 2030, the anticipated number of EVs on roadways is expected to reach 18.7 million, requiring the establishment of almost 9.6 million charging stations as shown in Fig. 1.2 [8]. However, the MG system can be used for balancing energy consumption across the different sectors. The MG systems provide reliable, economically viable, and ecologically sustainable electricity. Moreover, it enhances the stability as well as the effectiveness of the local electricity grid [9]. In summary, MG networks provide the optimal choice for mitigating energy costs, with the added advantage of the potential to sell generated electricity to the utility grid.

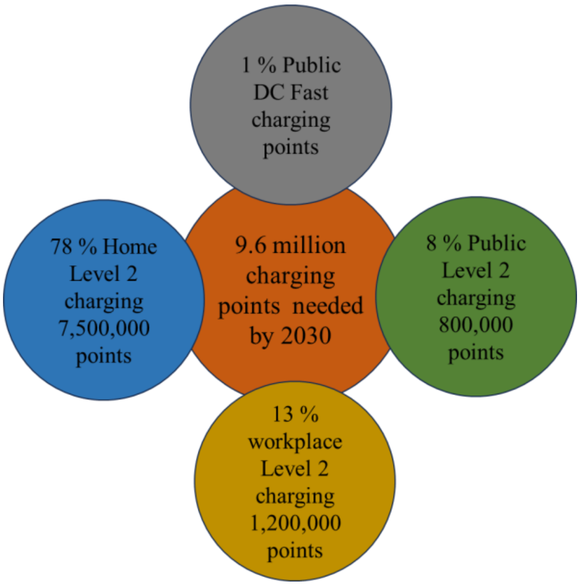

Figure 1. 2: EV expected charging station in 2030, taken and modified form [8]

Given the depletion of traditional resources along with the escalating need for energy generation, the implementation of an MG system has the potential to support the maintenance of continual production of energy. MG is frequently employed as a means of adding or offering supplementary electricity during moments of heightened demand. RESs, such as wind and solar, are frequently used by them. The integration of adjacent wind or solar resources in an MG has the potential to mitigate the utility system's susceptibility to localized incidents by ensuring redundancies for critical services [10]. Consequently, the integration of RESs into the distribution sector led to the emergence of terms such as distributed generation (DG) and distributed energy resources (DERs). By integrating these concepts and leveraging technological advancements, a novel grid configuration known as an MG was established [11].

The disruptions to the transmitting system in conventional power grids can result in a complete grid failure. On the contrary, due to their self-sufficiency, MGs have the potential to sustain the provision of energy to their respective community members even in the case of a primary grid failure. Integrating MG considerably benefits critical infrastructure, such as hospitals, military installations, and data centers. In addition, MG has the potential to enhance energy self-sufficiency, thereby diminishing users' reliance on fossil fuels and the primary power grid through the use of local energy sources like solar cells and WT. Consequently, there may be an improvement in energy security and a decrease in power prices. In addition, MGs can incorporate energy storage technologies like batteries, which may effectively manage the equilibrium between supply and demand, hence diminishing the need for traditional power plants [12]. Kamal et al. [13] conducted a study to examine the economic feasibility of MG in developing countries. The study suggested that MGs could serve as a viable method for delivering reliable and cost-effective electricity to rural people in developing nations. Regulations have a crucial role in the development and implementation of MGs. The study conducted by Feng et al. [14] examined the potential and challenges related to the regulation of MG in the united states of america (USA). The increasing prevalence of EVs poses a significant risk to the dependability of the energy system. Their study describes a hybrid EMS designed for a direct current (DC) -connected MG that relies on RERs and can facilitate EV charging. The system also incorporates battery energy storage technologies and a smart computer that can optimize energy flow and regulate EV charging. The authors believe that the proposed strategy effectively tackles the concerns regarding EV charging and grid strain [15].

The selection of appropriate optimization methods for problem-solving is dependent upon the accuracy of the provided input parameters. Consequently, a lack of precision in the estimation of random input variables will yield inaccurate outcomes. Nevertheless, the EMS and MG operation contains numerous unpredictable variables [16]. These unpredictable statistical factors involve several elements such as market power pricing and client demand for load. Consequently, it is imperative to assess the efficacy of conventional optimization methodologies within the novel context, and to reassess operational approaches in the face of unpredictability, with the aim of mitigating the risks inherent in MG construction and maintenance [17], [18]. Optimization methodologies can be characterized based on whether they possess a singular or several aims. For instance, in the field of MG-EMS, research may focus on reducing expenses and carbon dioxide emissions, or simultaneously improving both. Nevertheless, when optimization methodologies incorporate uncertainty modeling, the outcomes might be considered reliable [19], [20]. Attou et al. [21] suggested a unified EMS for a hybrid energy storage system (HESS) and connected MG. The primary aim was to mitigate fluctuations in demand as well as production patterns, while simultaneously improving the use of RESs and managing the transfer of energy with the utility grid. The application of a Rule-based EMS (RB EMS) was proposed by the author as a means to implement long-term EMS, including the day-ahead schedule of DERs, in a household multi-source grid-connected MG. The distributed controller simultaneously supervises the management of short-term electricity. The EMS optimizes the operational efficacy of the MG by proactively scheduling DERs to meet the required load while following various constraints. The findings from the installation and evaluation of the EMS in a simulated hybrid MG indicate its efficacy in reducing operational expenses and enhancing the resilience of the MG.

Intelligent computing enhances the management of primary grid energy use and results in cost savings for consumers. This study aims to examine residential systems that are capable of generating renewable energy. The residential energy infrastructure comprises of environmentally friendly energy technologies, a storage battery, and a connection to the primary power grid. By employing a storage battery, energy produced by any sustainable source can be used as required and subsequently sold to the power grid when the battery reaches its maximum capacity. Furthermore, this research used several conditions to assist the process of charging and discharging the battery. The determination of whether a battery should be charged or discharged was mostly based on the consideration of prices as a crucial element. For instance, in the event of low electricity rates, batteries will undergo charging, whereas greater electricity costs will result in their discharging. The charging status of the batteries is also given priority to RESs. The present work offers a cost-effective EMS for EVs within MG, employing the particle swarm optimization (PSO) algorithm. The aim is to determine the most cost-efficient strategy to allocate energy to EVs while considering restrictions such as battery state of charge, charging/discharging speeds, and power cost. PSO is a strong optimization approach that can effectively find optimal solutions in complicated, multidimensional search spaces. Furthermore, solving complicated and nonlinear optimization issues. In microgrid systems, which frequently feature nonlinearities and uncertainties owing to variables such as renewable energy sources and fluctuating demand, PSO's resilience assures consistent performance in optimizing system functioning.

1.1 Problem Statement

On-road vehicles cause a significant increase in CO_2 emissions, resulting in global warming. The utilization of solar PV and WT energy sources in EVs could be a prominent environmentally friendly alternative for on-road vehicles [22]. However, integrating these RESs into the grid has posed significant challenges due to their infrequent and unpredictable nature [23]. Furthermore, integration of these RESs on a larger scale requires an optimum combination of system operation, management, and adequate energy flow [24]. Therefore, this research seeks to find the optimum EMS in MGs for EVs using machine learning-based optimization models and apply the proactive technique to EV charging.

1.2 Aims and Objective

The suggested system utilizes solar and wind energy sources to generate electricity, supplemented with battery backup. By employing stored energy during outages, this combination guarantees a reliable power supply for organizations, homes, and commercial constructions.

This thesis aims to develop a system that assesses the efficiency of an MG in residential buildings by combining available DERs with different technologies like battery energy management systems (BESS) and EV charging stations, also optimizing the charging of EVs based on time and electricity cost. Thus, the objective of this study is to integrate PSO to provide a cost-effective method for managing EV energy in MG. PSO is a highly successful optimization technique for analyzing the stability, long-term viability, and efficiency of MG. This is due to its ability to handle complex constraints, real-time data, and numerous goals.

The main goals of this thesis are as follows.

To develop a PSO-based model for cost-effective EMS.

1. To propose PSO-based cost-effective EMS for EVs in MGs while analyzing multiple scenarios.
2. To incorporate the house-to-grid (H2G) functionality to save user expenses.
3. To address the financial and operational difficulties linked to the present incorporation of EVs into MGs.
4. To perform the proactive charging technique on EVs.

Chapter 2 - Liteurtare Review

This chapter includes a comprehensive literature review related to MG control procedures and EMS. The research focuses on the significant role of synchronized photovoltaic (PV) panels with the utility grid in circumstances involving solar radiation, dynamic consumer demand, and nonlinear load situations [25]. An MG is a small electrical generation and distribution system that may operate alone or in conjunction with the main grid. The inclusion of diverse DERs, such as alternative fossil fuel or diesel engines, PV, WT, and BESS, is a common practice in MGs [26].

2.1 Microgrid

An MG operates as a compact electrical grid, either individually or in combination with a larger grid, mostly consisting of DERs connected to a local distribution network [27]. Key DERs include PV WT, and BESS [28]. The effective operation of an MG necessitates the management of various resources, the equilibrium between energy demand and supply, and the maintenance of grid stability. Numerous scholarly works highlight the pivotal elements, including, EMS, load management systems, and the significance of uninterrupted power provision [29]. Current advancements in the field of networked MG systems have emphasized the utilization of communication platforms that are grounded in cloud theory and computing multi-objective optimization approaches. These advancements aim to improve the resilience and coordination of these systems. The term "balancing the supply of energy and demand" was employed by the author in reference [30]. The EMS assumes the responsibility of optimizing the efficiency of the MG operation. To adequately address the energy demand, it is imperative to effectively regulate the production of RESs and storage systems. For instance, in [31], DERs such as PV, WT, and energy storage devices produce and retain electricity. The MG system oversees the functioning of multiple DERs to provide a reliable and consistent power supply. The load control system described in [32] manages and regulates the energy consumption of various appliances and gadgets linked to the MG. This necessitates the management of consumption patterns and the allocation of loads according to their level of importance. As stated in [33], MG systems can be integrated into a larger power grid or operated independently. Within an energy system connected to a larger grid, the MG can interchange power with the larger grid to maintain a harmonious balance of energy demand and supply. MG has the potential to enhance system reliability, adaptability, and effectiveness, while also improving the ability to satisfy demand more efficiently [34]. The communications platform developed by the authors in [35] utilizes cloud theory to establish an efficient EMS for networked MG. The authors of [36] employed a computationally multi-objective optimization methodology to enhance the resilience of a networked MG through the utilization of distributed generators. The paper [37] presents a resilient distributed approach for efficiently managing operations across multiple interconnected MG under the control of a single operator. In [38], the energy interchange process across connected AC /DC MGs was depicted using an approach based on the alternate direction method of multipliers (ADMM). The authors in [39] investigated the energy transfer between interconnected MG by employing a bi-level linear programming method that took into account the demand response (DR) issue. Numerous scholarly investigations examine collaborative methodologies for energy management within MG. The integration of MGs facilitates the control of power in a reciprocating manner [40]. K. V. Vidyanandan [41] states that the integration of MGs enables the exchange of electricity in both directions. The implementation of RESs, such as PV and WT, inside the transmission sector facilitates the reintegration of electricity into the system. In addition, the implementation of an MG offers various advantages compared to the conventional grid such as [42], (a) the release of dangerous pollutants is reduced, (b) provides a consistent and regulated energy distribution to all loads, (c) it can function as an alternative power supply in the event of a power failure on the primary grid, and (d) the capacity to function in both connected and independent modes. Bagheri et al. [43] suggested a unique online control technique for DSTATCOMs in MG's using reinforcement learning algorithms. They attempted to improve power quality in MG's. The DSTATCOMs could dynamically react to changing conditions by using reinforcement learning, which improved voltage control and reduced harmonics. The study yielded improved power quality measures, such as lower total harmonic distortion and better voltage control. Additional research into reinforcement learning in power system applications and potential real-world implementation of the suggested technique is recommended.

2.2 Incorporation of DERs into Microgrid

DERs, such as alternative fossil gas or gasoline power plants, PV, and BESS, are commonly incorporated into MGs [26]. The primary objective of integrating DERs into the MG is to attain an optimal energy-effective and economically viable configuration, which includes the provision of maximum electricity at minimal cost, while simultaneously ensuring an equitable equilibrium between on-grid and off-grid circumstances. The majority of research in this field focused on established renewable energy technology, such as photovoltaic cells and turbines equipped with a BESS [44]. Yerasimou et al. [45] developed an arrangement that integrated PV systems with BESS. The configuration of the PV systems and BESS resulted in a combined electrical capacity of 35 kW and 10 kWh. The implementation of PV as the main source of electricity in the system necessitated the introduction of BESS to address the challenge of unpredictability, hence leading to enhanced energy utilization. To provide further clarification, in the event of an overabundance of energy generated, it is imperative to store it inside the designated storage system. They introduced their methodology based on their experiments, as it has the potential to enhance energy conservation and enable the MG to achieve self-sufficiency. When considering the distribution of wind power, this approach has been chosen over the implementation of PV systems due to its superior energy generation per unit. Moreover, certain studies [46] ascribed this phenomenon to the excessive expenses associated with power production. The incorporation of DERs and EV charging points into MGs raised substantial apprehensions on both consumption and supply aspects. Fouladi et al. [44], [47] examined the complexity of achieving optimal coordination of MG components. To enhance precision, the authors presented a power management methodology that revolves around the charging algorithm employed in plug-in hybrid vehicles. The innovative method, which underwent development and testing on a 33-bus test system, yielded a reduction in the energy transfer between the MG and the primary grid due to the increased energy generation by DERs. In addition, Fouladi et al. [48] enhanced previous studies by prolonging the useful life of BESS. Researchers utilized a 200-kWh lithium-ion battery with a 25% level of discharge in their experiment. The bilinear equations limitation was employed to configure the BESS in a manner that avoided simultaneous charging and discharging. Consequently, it was found that using the BESS at a higher state of charge (SOC) could potentially prolong its lifespan.

2.3 Grid- connected with BESS-PV-Wind

Grid-connected MG's offer a diverse range of potential advantages. One of the main advantages is in their ability to facilitate the incorporation of RESs into the power grid, thereby enhancing the proportion of clean energy and reducing GHG emissions. The enhancement of grid reliability and stability is achieved through the implementation of backup power systems and the mitigation of blackouts. In addition, electricity prices can be mitigated by the optimal utilization of local RESs and active engagement in DR initiatives. Furthermore, individuals have the potential to enhance the advancement of a smart grid through the enhancement of collaboration and interaction across diverse grid participants and equipment. Numerous research has provided evidence regarding the possible benefits associated with grid-connected MGs. The primary obstacle lies in achieving synchronization between the proposed system and the grid. However, the grid utility sync approach can be utilized to ensure the concurrent operation of the MG beside the primary grid [49]. The integration of RESs into MG can be challenging because to their inherent volatility and the need to coordinate their power generation with the grid. Renewable energy is used to generate electricity via PV and WT, while the BESS maintains standby electricity and power output balance. In contrast to a single RES, the integration of PV with WT offers a more reliable and obvious power provision. The careful examination of grid integration is crucial for incorporating wind and solar energy into an MG. Bagheri et al. [50] explored the effects of battery predictions on smart power systems, with an emphasis on incorporating RESs. They investigated by honey bee mating optimization (HBMO) the effects of precise battery forecasts on system performance and dependability. Their research provided insights into the optimization of renewable energy integration and grid stability. The study emphasizes the significance of better forecasting approaches for the optimum use of renewable resources in smart grids. The authors urge more study into improving forecasting accuracy and practical use in smart power systems for sustainable energy management.

Feng et al. [51] reported that, a grid-connected MG exhibited reduced power expenses and GHG emissions compared to a conventional grid. The authors investigated the potential of grid-connected MGs to contribute supplementary services to the grid, such as frequency regulation and voltage assistance. Zhang et al. [52] determined that these services have the potential to enhance grid stability and dependability while also providing advantages to MG consumers through reduced energy expenses. Although grid-connected MGs offer advantages, they also face several problems and disadvantages. For instance, the implementation of intricate management and control systems is necessary to achieve optimal coordination between the MG and the grid, thereby mitigating disputes and instabilities. One potential constraint on their utilization or efficacy is the presence of regulatory or technological impediments. Furthermore, because to the growing interconnection and data sharing between the MG and grid, there is a potential for an escalation in cybersecurity concerns [53]. Kumar et al. [54] conducted a study examining the financial and technological obstacles hindering the implementation of grid-connected MGs in India. They proposed a legal framework aimed at encouraging the use of MGs, while also resolving issues related to coordination and interconnection. The research conducted by Yan et al. [55] examines the security hazards associated with grid-connected MGs. The authors propose an integrated defense system that incorporates the detection of intrusions and machine learning techniques. Yang et al. [56] proposed a model with multiple objectives for a grid-connected MG in China. This model takes into account multiple variables such as financial, ecological, and social considerations. The researchers proved that this approach has the potential to yield substantial cost savings and carbon decreases while simultaneously enhancing service quality. Hassan et al. [57] examined the most efficient dimensions and placement of a grid-connected MG in Pakistan. They determined that this system has the potential to deliver dependable and cost-effective energy to rural regions, while simultaneously decreasing reliance on fossil fuels. System-connected MGs possess the capacity to provide numerous advantages, such as the incorporation of RESs, enhanced system resilience, financial savings, and the integration of smart grid functionalities. Nevertheless, they encounter a range of obstacles and drawbacks, such as difficult oversight and administration, technological and regulatory impediments, and cybersecurity weaknesses. Due to its emphasis on micro-integration, including the establishment of linkages to residential, educational, and commercial establishments, DG has the most promising prospects for integration within this particular industry. Therefore, the examination of the implementation of MG in residential buildings and commercial complexes has captured the interest of scholars. Numerous studies have been carried out to examine the effectiveness, efficiency, and optimization of grid-connected MGs, utilizing various modeling and simulation methods, as well as real-world examples and cases.

The study conducted by Kermani et al. [58] focused on the development of a scheduled energy hub. The objective was to determine the optimal power arrangement for different elements and demand profiles, taking into consideration the DR. The significance of this study lies in its emphasis on the self-scheduling algorithm, which aims to reduce electricity expenses by charging BESS in times of low demand and draining them during peak hours. In their testing, they also considered the DR. Consequently, they achieved a cost reduction of up to 37.5%. The entry and exit of BESS is vital in an isolated MG. Due to the lack of connection between the separated MG and the main grid, it is necessary to accurately allocate the energy supplied by DERs and BESS throughout the load and BESS. In this particular scenario, the selection of an appropriate battery capacity is fundamental. A study by [59] examines the optimal estimation of energy capacity frameworks. The case under consideration encompassed WT engines, PV clusters, plug-in hybrid electric vehicle (PHEVs), and the lead-based BESS. They evaluated grid-to-vehicle (G2V) and vehicle-to-grid (V2G) options to provide an appropriate BESS scaling method. Consequently, it was determined that the maximum level of control that BESS should provide to sustain all loads is 2174 kW.

2.4 Demand response under dynamic conditions

The implementation of demand-management technologies, such as DR, has become a feasible approach to providing a reliable and steady energy provision. Customers can employ DR to manage their energy consumption under fluctuations in energy prices and grid circumstances. Integrating DR into electrical systems under uncertainties can pose challenges due to several reasons, including the unpredictability of RESs, volatile markets, and customer behavior [60]. The objective of DR is to redirect energy usage from periods of high demand to periods of low demand, resulting in a decrease in the system's overall consumption and an enhancement in system effectiveness. Moreover, there could be ambiguity concerning the marketplace, supply, and consumption of energy in the drought-prone region [61]. The uncertainty around energy demand persists due to the inherent challenges in precisely forecasting consumer choices and utilization trends. Supply instability refers to the inherent unpredictability associated with RESs, including solar and wind power. Moreover, market uncertainty arises from fluctuations in energy expenses and legislative measures. Numerous scholarly investigations have examined the suitability of DR in various scenarios characterized by energy unpredictability. Wang et al. [62] proposed a two-stage stochastic DR model that considers energy DR in the presence of unpredictability. The objective of the study was to determine the optimal power pricing by manipulating the load through the introduction and removal of different equipment, thereby introducing a level of unpredictability. They demonstrated that incorporating energy DR with uncertainties into the model leads to a more resilient DR strategy that can effectively manage unforeseen fluctuations in energy demand. As a consequence, there was a reduction of 15% in electricity expenses in comparison to the probabilistic model. To address the energy demand and account for inherent unpredictability, the researchers in the study by [63] incorporated RESs, such as wind turbines (WT) and solar electricity, into the MGs. The researchers proposed an optimization challenge and made adjustments to the variables by employing a modified virus colony search (VCS) technique. To assess the suggested approach, MG systems are employed in various situations to analyze the influence of the DR program on the overall decrease in costs. Consequently, the implementation of DR led to an augmentation in voltage drops (up to 1.4%) and power variation (up to 1.2%), thereby resulting in a substantial reduction in the overall energy expenditure by up to 20-25% in comparison to the scenario when DR was not employed. The robust optimization technique proposed by Mauro O. et al. [64] provides an extensive structure for the day-ahead best-practice scheduling of an MG that incorporates batteries, variable loads, PV, and thermal energy output. Before solving a mixed-integer linear programming (MILP) problem, the system was divided into two phases utilizing a column-based and restriction production technique. The results of their study demonstrated that their suggested framework effectively addressed the MG optimization problem. They emphasized the importance of considering uncertainty, as a 15% error in load and PV generation estimation led to a 29.8% increase in daily operation costs. In summary, the results of this study suggest that energy uncertainty should not be disregarded, even when incorporating DERs, and that DR is a crucial instrument for effectively controlling these uncertainties. Moreover, DR can contribute to the preservation of the grid's dependability and steadiness, decrease expenses, and mitigate ecological consequences by synchronizing the supply and demand equation, diminishing the necessity for additional power-producing services, and advocating for energy efficiency and preservation. The significance of DR will grow as energy systems progress and new obstacles emerge in providing a reliable and sustained energy supply.

2.5 Energy Management System (EMS)

This section considers the comprehensive evaluation and examination of multiple energy management techniques that can be implemented in various MG networks. This review and analysis will look at the goals, limitations, and methodologies of each plan, along with optimization techniques and software for simulation. Furthermore, it examines existing obstacles and proposes potential avenues for future research [65]. Effective EMS is essential for MG systems to ensure dependable and efficient operation, save energy expenses, and mitigate GHG. Aside from energy storage techniques that store surplus energy for future utilization, MG systems can optimize energy output by utilizing a diverse array of RESs, including solar, wind, and hydropower. Efficient DR plays a crucial role in achieving equilibrium between energy supply and demand within MG systems. [66]. Intelligent management systems can be employed to regulate energy use and remove excessive loads during instances of heightened demand. Battery exemplifies a technological innovation that enables the simultaneous provision and storage of energy during periods of high demand, as well as the preservation and use of energy during periods of shortages. By implementing this, the energy usage is decreased and the dependability of the MG system is enhanced. DR methods can effectively decrease the use of energy during periods of high demand. This objective can be achieved by providing consumers with opportunities to reduce their energy consumption within designated time intervals. The integration of MG systems with the main grid has the potential to enhance energy security and yield cost savings. The present study aims to examine the techno-economic implications associated with renewable energy, electricity expenses, and grid integration. The main objective of this study is to develop a DR system that optimizes the advantages for MG clients. To identify the appropriate incentive value, a detailed optimization technique is implemented. The utilization of an innovative intelligence algorithm is then employed to reduce the overall expenditure of an MG, and the results are compared between the presence and absence of a DR program. Cost difficulties encompass several factors such as fuel prices, penalties for pollution, expenses related to infrastructure upkeep and operation, capital charges, and other related expenditures [67]. Abedinia et al. [68] investigated the optimal architecture of an energy hub to support numerous smart energy system participants and electric automobiles. They used synergistic ways to improve efficiency in this situation. Through their study, they gained a thorough grasp of the complexity involved in optimizing energy hub designs for a variety of stakeholders. Their work emphasizes the necessity of collaboration and integration among diverse participants in smart energy systems, as well as the need to include electric cars in energy hub designs. The report proposes more research into joint optimization methodologies for maximizing efficiency and sustainability in smart energy systems. The management of energy flow between the MG and the main grid can be accomplished through the utilization of advanced control technology. In general, the efficacy of MG systems is reliant upon the proficient management of energy resources. The enhancement of MGs can be achieved through the integration of RESs, battery storage, and intelligent control systems, resulting in a reliable and efficient power supply, as well as a reduction in energy costs and emitted GHGs.

2.6 HOMER software

This study uses hybrid optimization of multiple energy resources (HOMER) software as a well-established industrissal platform to explore and replicate diverse scenarios and conduct numerous case studies by [69]. This software stands out from others since it includes peer-reviewed resources for solar global horizontal irradiance (GHI) index, wind speed, and stream discharge. This, in turn, may be utilized to create an optimum and hybrid MG design that incorporates DERs such as PV, WT, hydropower facilities, and conventional power plants. HOMER can also give the setup cost profiles for economic analysis. Overall, HOMER software proved beneficial in developing an efficient configuration for both on- and off-grid scenarios.

Chapter 3 - Methodology

3.1 Methodology

3.3.1 Overview

This EMS aims to effectively distribute the use of locally produced renewable energy, grid electricity, and BESS to minimize expenses and optimize the usage of sustainable resources. The research includes a thorough examination, taking into account both grid-connected and MG circumstances and analyzing multiple potential scenarios within each.

3.3.2 Micro Grid and Energy Management System

The established MG system consists of several components, such as the utility grid, WT, PV, and BESS these resources are used in DERs. The utility grid serves as the fundamental infrastructure, ensuring a reliable supply of electricity when there is insufficient generation of renewable energy. WT and PV panels are components of renewable energy that collect wind and solar energy, respectively. BESS has a crucial function of storing surplus energy when it is generated in large amounts and releasing it when there is high demand or low output of renewable energy. In addition, the system integrates diverse RESs to establish a robust and adaptable energy infrastructure.

The EMS is the central component of this complex system, performing as an advanced control system. The EMS actively manages the distribution of electricity to household appliances and EV charging points. It maximizes the allocation by considering real-time criteria such as the present demand for electricity, the cost per unit of power, and the condition of the BESS. This dynamic decision-making mechanism provides a smart equilibrium between cost-effectiveness and sustainability, in line with the research’s primary objective of decreasing expenses while optimizing the exploitation of renewable resources inside the MG. Fig. 3.1 shows the EMS utilized in this study.

3.3.3 BESS Strategic Approach

The BESS strategic strategy, as shown in Fig. 3.2, has also been developed to optimize the use of RESs. This approach involves multiple scenarios, as discussed below:

Scenario 1:

Excess renewable energy: Surplus renewable energy occurs when the energy generated exceeds the amount needed. In such cases, the system assesses the battery's SOC. When the SOC is less than 100%, any extra power is utilized to recharge the battery. If the SOC is already at 100%, any additional power is supplied back to the grid at lower costs.

Scenario 2:

Insufficient renewable energy: If there is not enough renewable energy available, the algorithm will change the price of the power grid in response to the fluctuations in demand over time. During times when there are reduced grid rates, the battery is given priority for charging, and during times of higher costs, the battery discharges until it reaches a predetermined lower threshold.

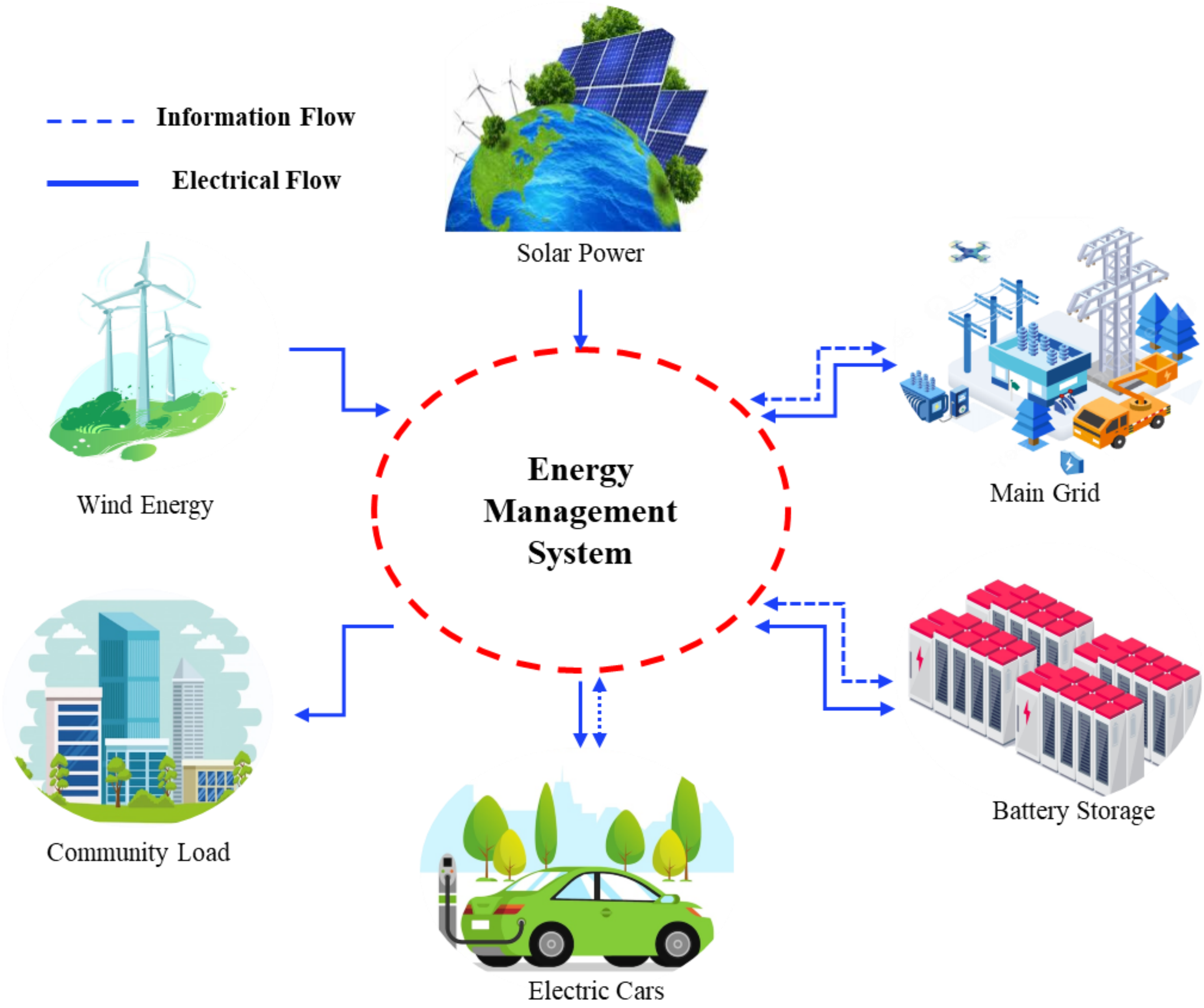

Figure 3. 1: Proposed Model for EMS

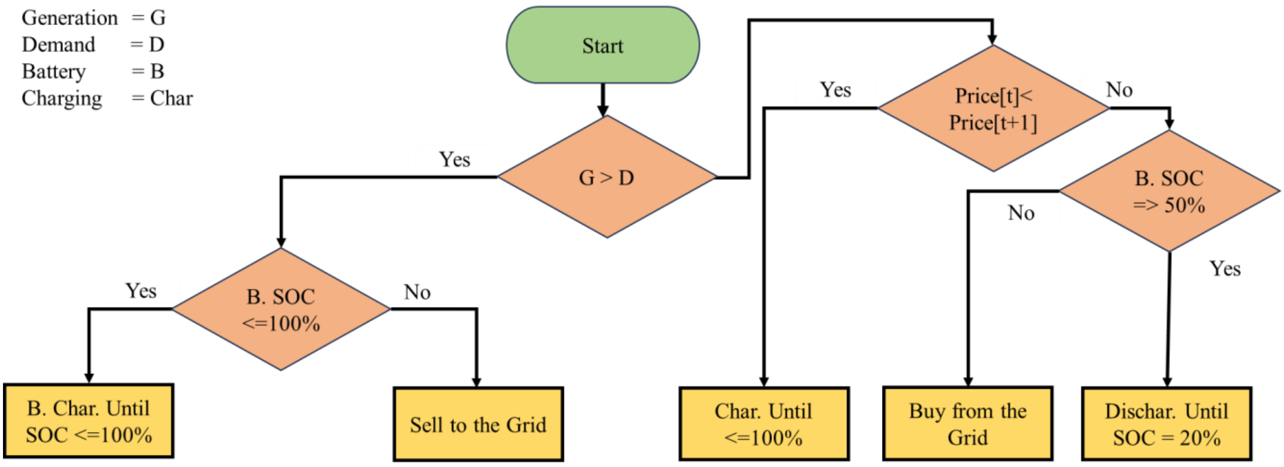

Figure 3. 2: Strategic rules used for BESS

3.3.4 PSO-based Optimization

The study utilizes the PSO method as an effective meta-heuristic methodology to optimize the charging and discharging schedules of BESS in the MG system. PSO simulates the collective behavior of a group of particles as they navigate through a search space to find the most optimal solution. inside this framework, each "particle" symbolizes a prospective solution inside the exploration domain, and the combined motion of particles is directed by their encounters and the most optimal solution known globally. By employing an iterative approach, PSO can effectively navigate and reach optimal solutions, which makes it highly suitable for the dynamic and intricate characteristics of MG energy management.

In 1995, J. Kennedy [70] developed the PSO, a nature-inspired optimization approach. PSO employs a swarm-based exploration approach to determine the global optimum. The motivation comes from the behavior of birds. Particles are pushed over the exploring area to find the appropriate population to achieve the challenge. Particles emerge in a multidimensional exploration area and move based on previous information and neighboring particles' positions. Additionally, particles are guided by the ideal place they and their neighbors have attained. It has a significant search capability in terms of candidate resolution spaces. This optimization approach offers advantages such as improved accuracy, ease of operation, fertility, and the capacity to produce random velocities for particles in the exploration space. PSO is a hybrid method combining genetic and evolutionary algorithms. To compute the function with new waypoints for a particular iteration, the position and velocity of each particle are adjusted. The PSO-based algorithm for optimization works in conjunction with the MG hourly demand needs and variable electricity pricing. PSO optimizes the MG operation by adjusting the duration of EV charging cycles based on the central grid power prices. This ensures that the MG works most cost-effectively, reducing expenses related to electricity usage. This method not only leads to cost savings but also supports the research's environmental goals by increasing the use of locally produced renewable energy. The utilization of PSO-based optimization enhances the adaptability, adaptability, and ability of the MG system to respond quickly to fluctuating conditions. This demonstrates the flexibility and effectiveness of this meta-heuristic technique in managing energy for EVs in a community location.

3.2 MGs Modeling

Create distinct adaptable designs for the various MG setups in this research study. This study will have an opportunity to determine the most optimal MG design in various circumstances and discover low-cost EV charging hours in different situations by constructing multiple adaptable designs. PV components, WT, BESSs, and the grid are inputs in the simulation designs, with house load and EV charging serving as outputs. The first design includes a PV array, WT, and utility grid as an input and house load as an output, see Fig. 3.3.

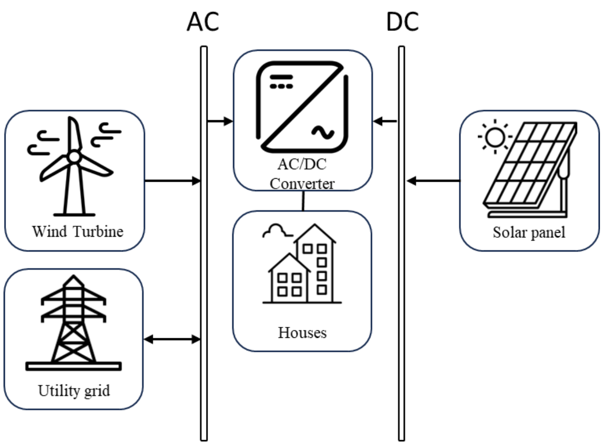

Figure 3. 3: First MG Design

The second design upgrades the first model by integrating EV charging as an output with house load, see Fig. 3.4. The third design includes a PV array, WT, BESS, and utility grid as an input and house load as an output, see Fig. 3.5; the fourth design upgrades the third model by integrating EV charging as an output with house load, see Fig. 3.6.

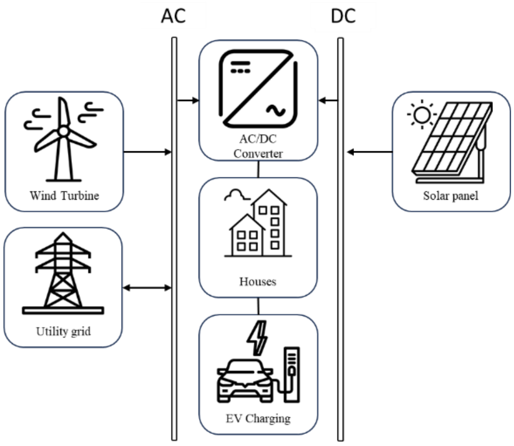

Figure 3. 4: Second MG Design

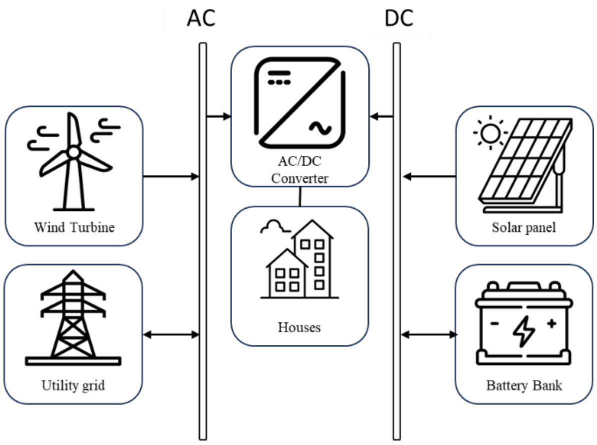

Figure 3. 5: Third MG Design

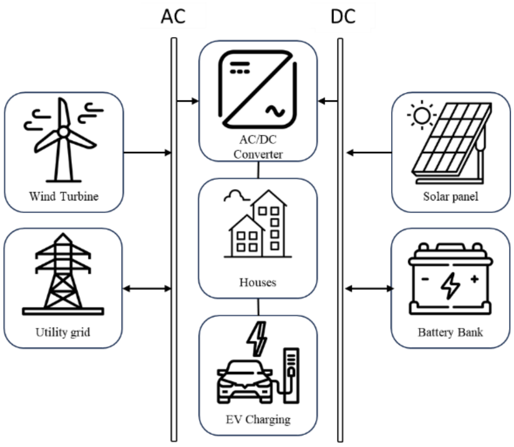

Figure 3. 6: Fourth MG Design

3.3 Mathematical Modeling

3.3.1 Photovoltaic Array (PV)

There are several elements that can affect the effectiveness of solar energy systems. Designing a solar energy system involves considering irradiance and temperature characteristics. The photovoltaic array's output power is directly correlated with sun irradiation and the generated power given by:

$$P_{pv}^{t} = \eta_{pv} \times N_{pv} \times P_{mpv} \times \frac{G^{t}}{G_{o}} \tag{3.1}$$

For evaluating the generated PV power, see Fig. 3.7, which is contingent upon solar radiation at the time G^t, P_{pv}^t is the produced power of PV arrays (W) at each hour, η_{pv} is the PV modules efficiency, P_{mpv} is the rated power of each PV (W), N_{pv} is the optimum size of PV, and G_o is 1000 (w/m^2) [71]. This dataset is from Burlington, USA, with a Latitude of 44.47 and a Longitude of -73.21 [72].

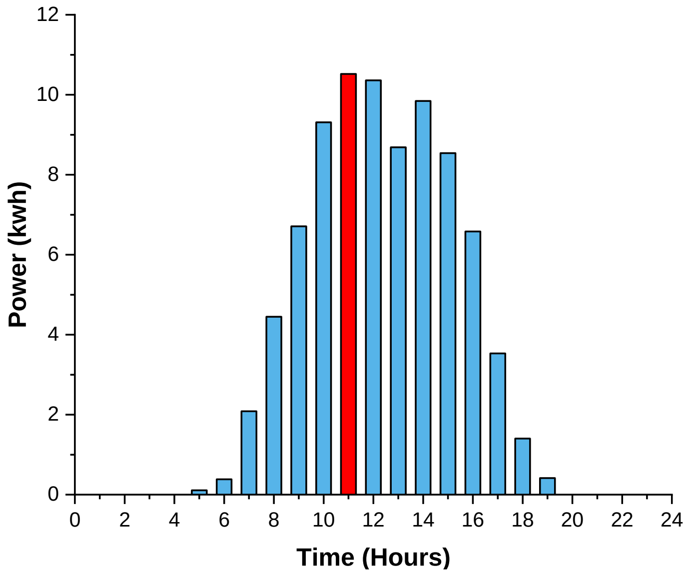

Figure 3. 7: PV output

3.3.2 Wind Turbine Generation (WT)

Wind energy encompasses the numerous forms of wind energy systems and components. Wind energy systems use two types of turbines: horizontal-axis wind turbines (HAWTs) and vertical-axis wind turbines (VAWTs). HAWT blades rotate on a horizontal axis using a horizontal rotor shaft [73] shown in Fig. 3.8. The rotor hub and blades, usually composed of fiberglass or carbon fiber, are connected by a blade root [74]. After that, the gearbox is attached to the rotor hub, which causes it to spin from low to high speed faster than the generator. The generator then transforms the mechanical energy of the rotor into electrical energy [75].

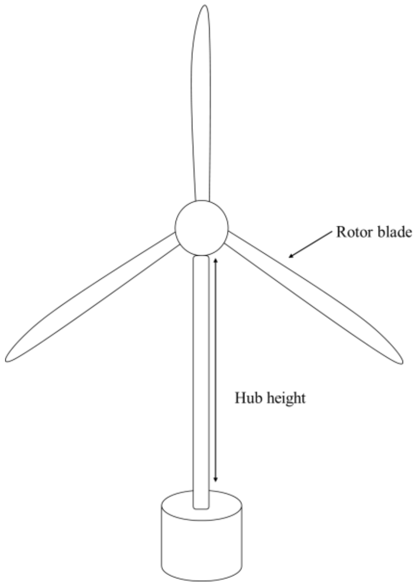

Figure 3. 8: Horizontal axis wind turbine blade (HAWT).

VAWT blades circle a vertical axis and are coupled to a vertical rotor shaft shown in Fig. 3.9. Turbines might be drag or lift type. Drag-type turbines include curved blades, whilst lift-type turbines have flat blades. VAWTs are less prevalent than HAWTs, although they have a few advantages over HAWTs, including the capacity to function in windy conditions and ease of maintenance [76].

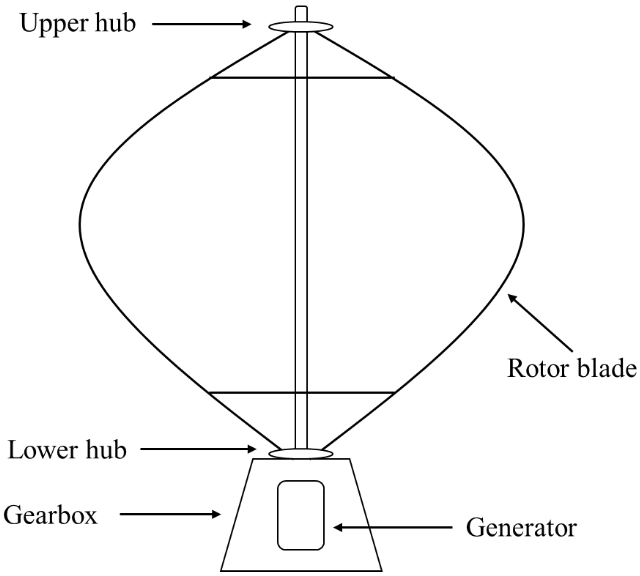

Figure 3. 9: vertical axis wind turbine blade (VAWT)

WT power generation depends on various elements, including cut-out and cut-in wind speed which can impact output power and efficiency. The WT generates AC electricity converted to DC using the converter. The output power of the WT shown in Fig. 3.10 is related to wind speed.

$$\begin{cases} 0 & V_w \leq V_{ci}, V_w \leq V_{co} \\ P_{w,ra} \times \left(\dfrac{V_w - V_{ci}}{V_{ra} - V_{ci}}\right)^3 & V_{ci} < V_w \leq V_{ra} \\ P_{w,ra} + (V_w - V_{ra}) \times \dfrac{P_{w,co} - P_{w,ra}}{V_{co} - V_{ra}} & V_{ra} < V_w < V_{co} \end{cases} \tag{3.2}$$

where, $P_{w,ra}$ and $P_{w,co}$ the WT's output power levels at its cut-out and rated speeds are represented by kW, respectively. V_w, V_{ra}, V_{co}, and V_{ci} show the wind speed in m/s for the measured, rated, cut-out, and cut-in, respectively [77]. This dataset is from Burlington, USA, with a Latitude of 44.47 and a Longitude of -73.21 [72].

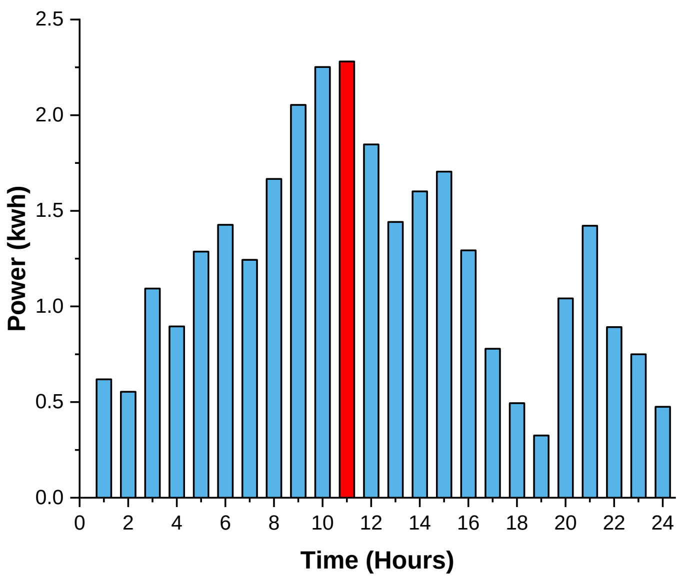

Figure 3. 10: Wind Turbine Output

3.3.3 Battery Energy Storage System (BESS)

The energy storage algorithm created for the thesis aims to lower power prices and reliance on the main grid by supplying stored energy from RESs and the grid. It was designed to analyze energy market pricing from the current hour to the upcoming hour and then determine whether to charge or discharge the battery.

The stochastic load profile of PHEV and the intermittent output power of RESs are reduced using a lead-acid BESS. Several conditions must be fulfilled to charge and discharge the BESS as follows.

$$SOC_b^{min} \leq SOC_b(t) \leq SOC_b^{max} \tag{3.3}$$

$$SOC_b(t_0) = SOC_b(t_{24}) \tag{3.4}$$

$$P_{BESS}(t) = \begin{cases} B_{Char}, if P_{gen}(t) > P_{dem}(t) \\ B_{dischar}, if P_{gen}(t) < P_{dem}(t) \end{cases} \tag{3.5}$$

where, SOC_b^{max} and SOC_b^{min} are the BESS's minimum and maximum SOC boundaries, respectively. To increase the lifespan of the BESS and prevent damage, the SOC of the BESS needs to fulfill the following requirements [79]. The difference between the BESS's charging and discharging powers can be referred to as its output power, provided that it stays within its permitted bounds.

$$P_{ch}^{max} \leq P_{out}(t) \leq P_{dh}^{min} \tag{3.6}$$

$$P_{out}(t) = P_{dh}(t) - P_{ch}(t) \tag{3.7}$$

3.3.4 Load Demand Modeling (LD)

The daily demand profile was calculated by adding energy consumption estimates from residential buildings, offices, and an EV charging station.

$$P_{LD}^t = P_{H.load}^t + P_{EV}^t \tag{3.8}$$

where $P_{H.load}^t$ and P_{EV}^t are the demand profiles of houses and EV charging, respectively.

3.3.5 Power Generation Modeling (PG)

To generate an energy generation profile for DERs, the daily energy output is made using PV arrays and WT. The hourly energy generation is computed by adding the output of all energy sources.

$$P_{PG}^t = P_{PV}^t + P_{Wind}^t \tag{3.9}$$

3.3.6 Objective Function

The suggested power management technique is formulated and provided in this section. To reduce dependency on the MG and offer reasonably priced EV charging. It entails gradually increasing the PHEVs' charging power for a day.

The primary aim of the recommended optimization approach is to obtain the most economical configuration for the MG system while meeting the system's overall requirements. Energy optimization management aims to decrease overall expenses, including pollution and power generation costs while satisfying network load needs. The mathematical expression for the objective function is given as.

$$F_{Minimize}^{t} = P_{pv}^{t} + P_{wind}^{t} + P_{Grid}^{t,c} + P_{BESS}^{t} - P_{H.Load}^{t} - P_{EV.Load}^{t} \quad (3.10)$$

where, P_{pv}^{t} is the PV output, P_{Wind}^{t} is the wind output, P_{BESS}^{t} is the battery power, P_{Grid}^{t} is the grid generation, $P_{H.Load}^{t}$ is the house load, $P_{EV.Load}^{t}$ is the EV load and the time is 24 hours.

Chapter 4 - Simulation Study, Results Analysis and Discussions

This chapter shows the simulation results of several scenarios, each indicating a distinct availability of renewable resources. Burlington (USA) was chosen as a case study while considering the four seasons (summer, winter, autumn, and spring). The simulation uses MATLAB to assess the effectiveness of an MG control system that integrates RESs such as PV, WT, BESS, house load, EV, and the main grid. Simulations were run in discrete mode to provide precise findings for each scenario. For the demand and generation profile data set taken from Burlington, USA, the Latitude is 44.47, and the Longitude is -73.21 [72]. The case study is explained in detail as follows.

4.1 Inputs for Simulation Study

The inputs used in the database are presented in Figure 4.1 showing that the winter peak demand for houses is 14 kW, whereas the EV charging peak consumption is around 6 kW. Figure 4.2 shows that the spring peak demand for houses is 12 kW, whereas the EV charging peak consumption is 6.6 kW. Similarly, it can be noted that the autumn peak demand for houses is 14.5 kW, whereas the EV charging peak consumption is around 6 kW shown in Fig. 4.3. Further, the summer peak demand for houses is 15.7 kW, whereas the EV charging peak consumption is 6.4 kW as shown in Fig. 4.4.

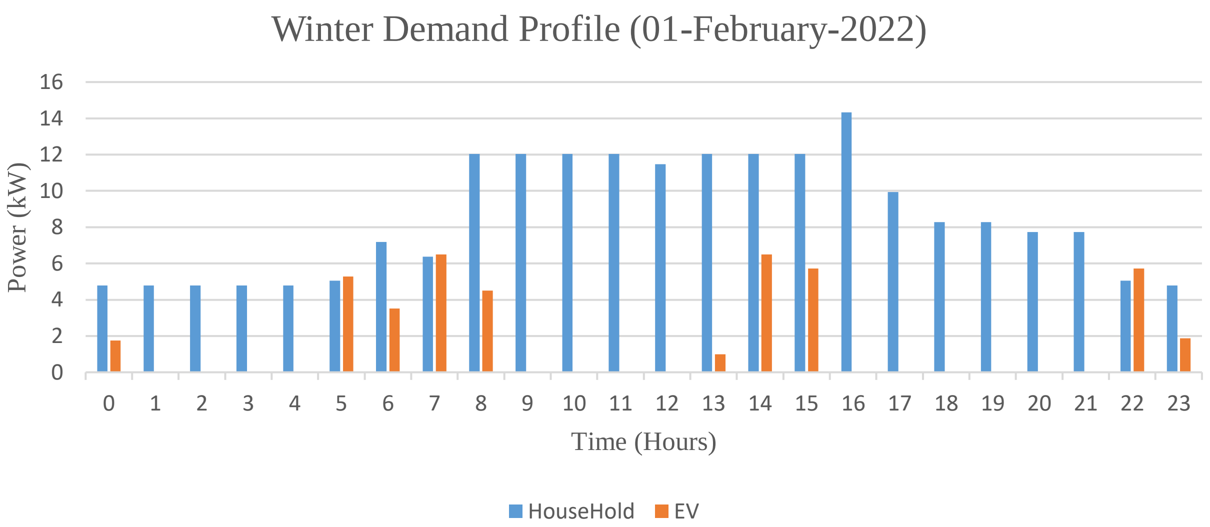

Figure 4. 1: Daily demand profile of Winter

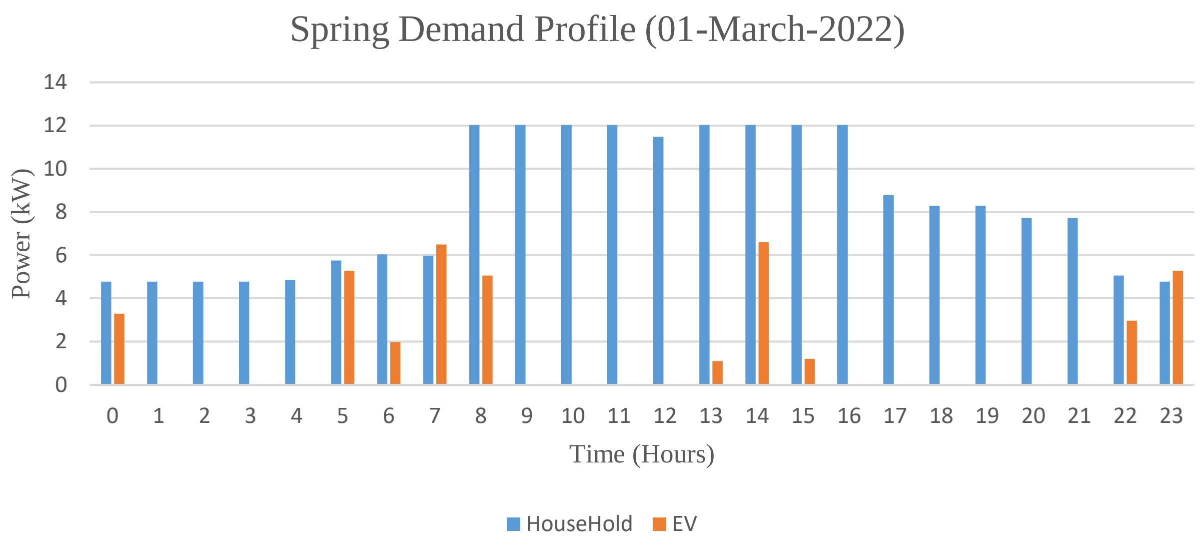

Figure 4. 2: Daily demand profile of Spring

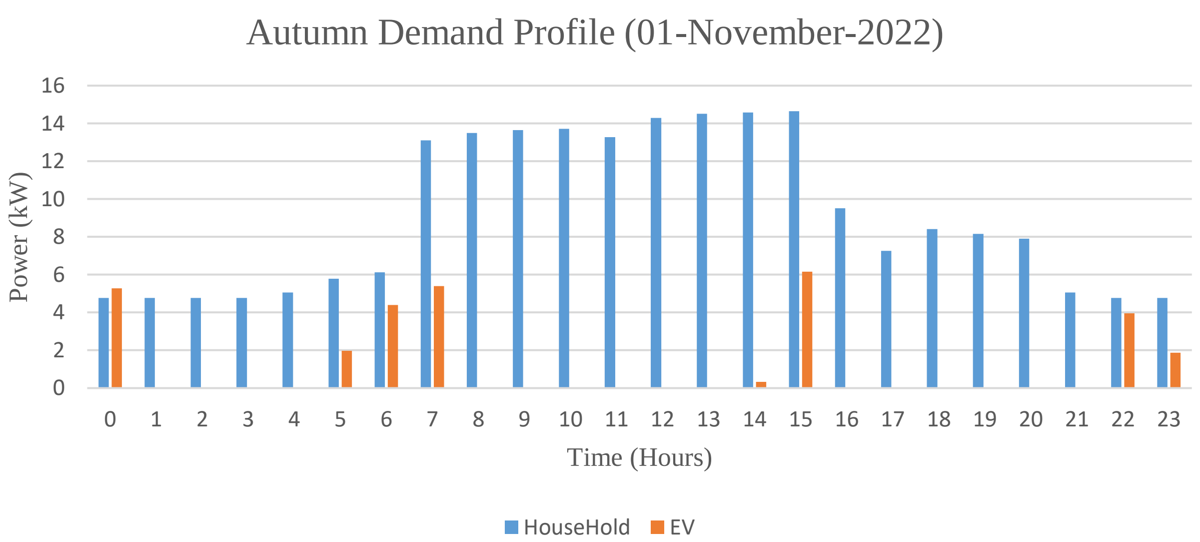

Figure 4. 3: Daily demand profile of Autumn

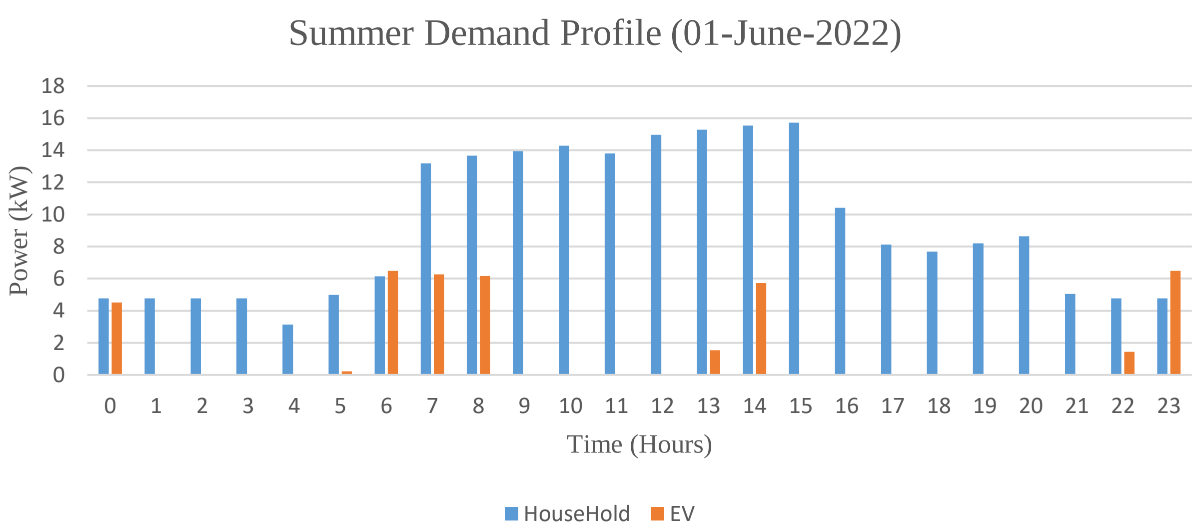

Figure 4. 4: Daily demand profile of Summer

4.2 Energy output profile

Figure 4.5 shows the energy generation by using PV for all seasons. Peak generation in winter is 8.5 kW, spring is 9.1 kW, autumn is 9.3 kW, and summer is 12.6 kW, whereas the WT peak generation in winter is 5.4 kW, spring is 4.3 kW, autumn is 5.6 kW, and summer is 4.1 kW shown in Fig. 4.6.

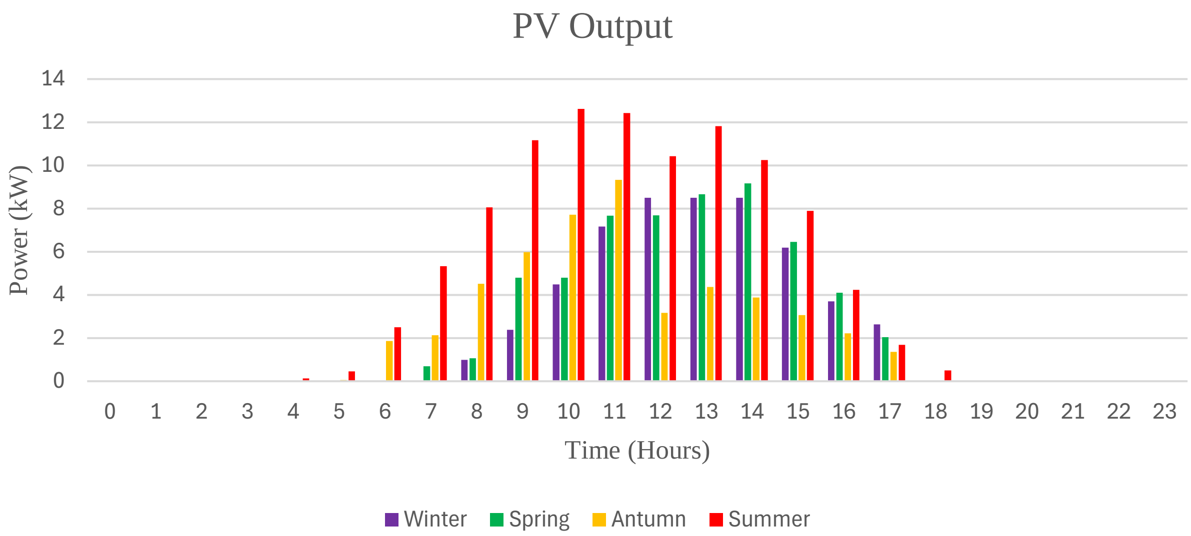

Figure 4. 5: Daily PV generation in all seasons

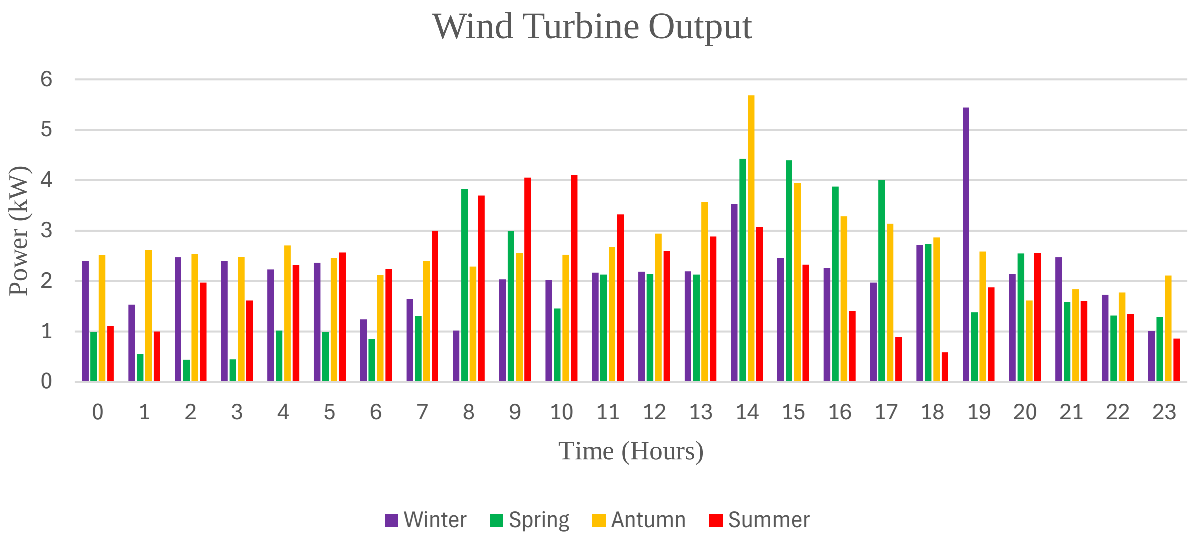

Figure 4. 6: Daily wind generation in all seasons

4.3 Simulation Studies

After generating the database, simulation experiments were conducted using 16 scenarios for four seasons with different MG designs. Differences in case studies based on the seasons and MG designing. In addition, a BESS charging and discharging algorithm is included to optimize energy costs. To be more specific, it was built in such a way that the BESS should be charged or discharged, dependent on the comparison of the power price of that hour and the following hour. Moreover, the system also optimized the EV charging hours based on electricity cost. For simulation, the PSO optimization technique was used in MATLAB.

4.3.1 Case Studies

This study considered multiple case studies, and the PSO technique was used to create the best scheduling mode for EV charging, aiming to produce a more optimized EMS. The suggested MG EMS, which integrates RESs, including PV, WT, BESS, EV, and the main grid, is evaluated using a MATLAB algorithm simulation. Several scenarios are implemented to see how the EMS behaves in power-sharing across various sources in all operational modes (electricity pricing, BESS SOC, house load, and EV charging time frames). For this simulation, we took 24 hours to test the different scenarios. The SOC_{min} and SOC_{max} are 20% and 80%, respectively in all case studies. Depending on the amount of sun irradiation, the solar system operates in all modes with a regular distribution over the day, peaking in power at noon. Throughout the day, there are peaks and troughs in the wind generation due to the wind speed, which varies randomly.

4.3.2 Winter season

4.3.2.1 Case Study 1 (PV, Wind, and Grid)

The daily load curve displays a 14 kW maximum power output for the house and 6 kW for the EV. The load profile fluctuates throughout the day and weather, with strong demand periods in the morning and evening and low demand throughout the night. When the MG runs without BESS, WT, and the main grid supply load in the morning when energy prices are low. Then, the PV system produces energy to satisfy the demand for housing load. At the same time, the power produced by the grid decreases, as shown in Fig. 4.7. The grid works with the WT to supply electricity as PV production decreases. The energy demand is low at midnight then WT provides the power this time. All the energy needed to meet the electricity demand is obtained from the grid, resulting in extremely high purchasing costs. In this case, receiving power from the grid is high at 9 AM is around 10 kW and the lowest power at 3 PM is 0.005 kW, and no return power to the grid because PV and WT power are not enough.

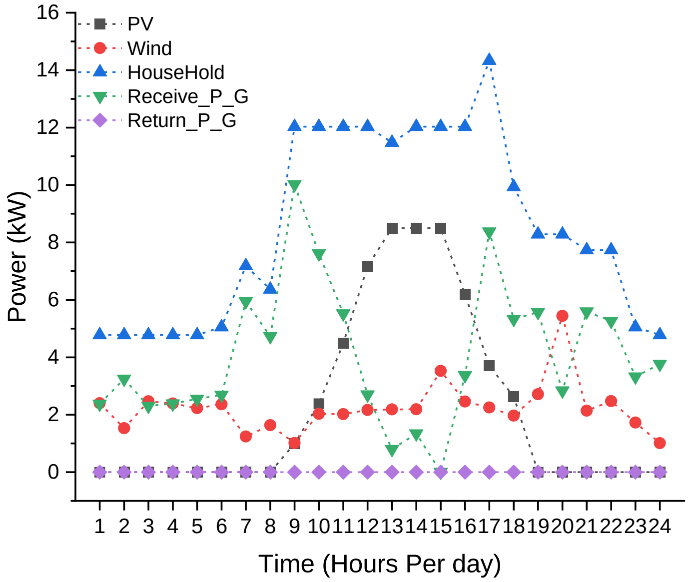

Figure 4. 7: Winter hourly power variation with House load and Grid import, return power

Figure 4.8 shows when adding the EV load to the house load, the import power from the grid increases. When operating in this mode, the system becomes less affordable outside of periods of renewable production when all demand is met by purchasing electricity from the grid due to the lack of storage mechanisms (stationary BESS). In this case, receiving power from the grid is high at 9 AM is around 15 kW and the lowest power at 1 PM is 0.7 kW, and no return power to the grid because PV and WT power is not enough.

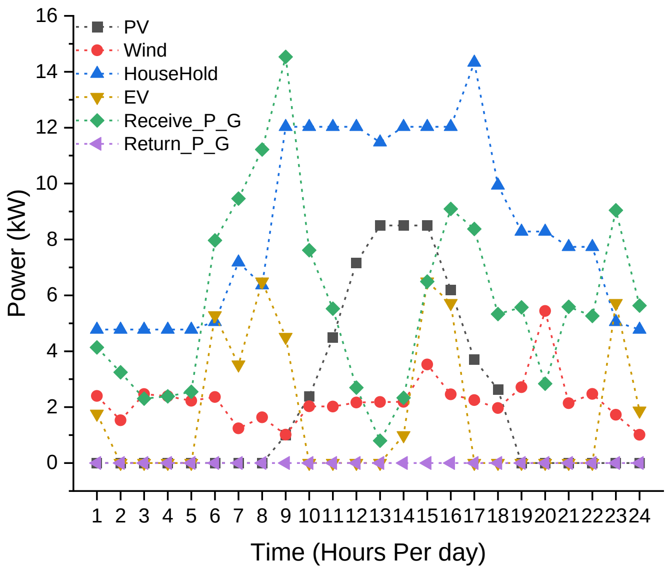

Figure 4. 8: Winter hourly power variation with House, EV load, and Grid import, return power

4.3.2.2 Case Study 2 (PV, Wind, BESS, and Grid)

In another case study, to take advantage of the cost-effective energy pricing, the grid and WT work together to meet the demand and enable the charging of batteries before sunrise. The objective of this method is to ensure that the SOC remains between 20% and 80%, with a minimum limit of SOC_{min} below 20%.

$$P_{pv} + P_{wind} > Load \tag{4.1}$$

$$P_{pv} + P_{wind} < Load \tag{4.2}$$

In scenarios when more electricity is produced than consumed, PV and WT systems are used to meet the demand, giving preference to using excess power from renewable sources. In this instance, surplus energy is used to raise the BESS SOC to its SOC_{max} limit at a reasonable cost when BESS is not fully charged. The remaining surplus energy will be used as a second priority: power return to the grid. Initially, the analysis was performed without implementing optimization techniques, as shown in Fig. 4.9. The total power received and returned can be noted as 113.3 kW and 4.09 kW, respectively. Additionally, per day cost was calculated (8.18$ without optimization) as presented in Table 4.1.

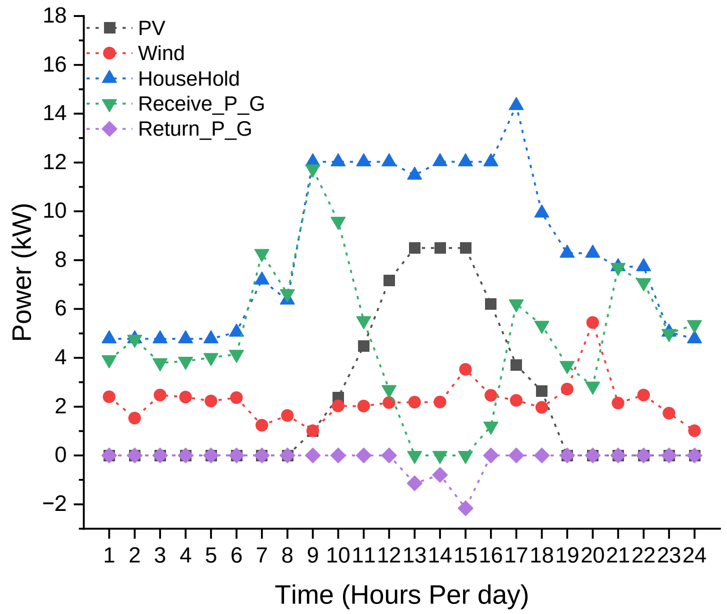

Figure 4. 9: Winter hourly power variation with House load, and Grid import, return power without optimization

Figure 4.10 shows the optimized power received and returned from the grid as 103.1 kW and 8.3 kW, respectively. The per-day cost for this case can be noted as 6.41 $. It can be observed that optimization results in a 21% reduction in price. In this case, using the BESS with renewable resources and receiving power from the grid is highest at 5 PM, around 12 kW, and the lowest at 7 PM is 1.5 kW.

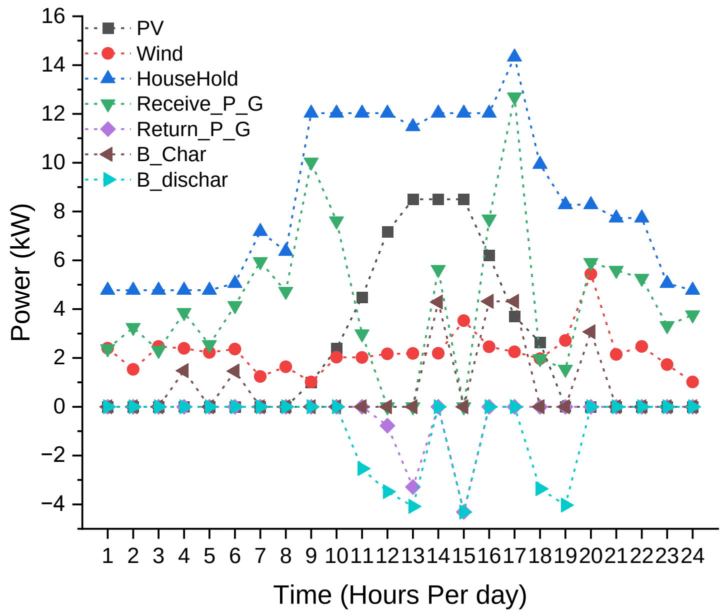

Figure 4. 10: Winter hourly power variation with House load, and Grid import and return power with optimization

If an EV is available without optimization, the total received power from the grid is 152 kW, the total returned power to the grid is 1.1 kW, and the day cost is 11.03 $, as shown in Fig. 4.11 and Table 4.1, respectively.

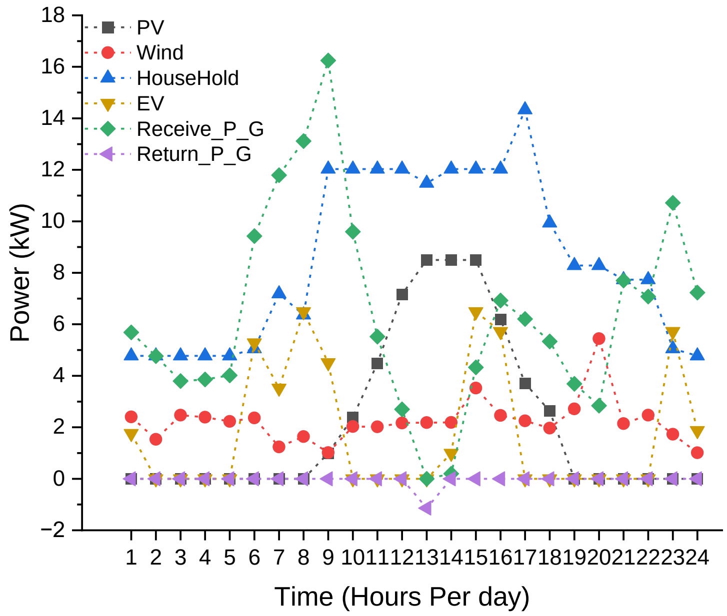

Figure 4. 11: Winter hourly power variation with House, EV load, and Grid import and return power without optimization

If an EV is available after charging the BESS, the remaining power is initially used to charge the EV battery, and if it remains in excess, it will be returned to the grid. The BESS begins to discharge to make up the power deficit when demand exceeds consumption. The BESS and the WT feed the load to its ultimate SOC_{min} limit. Using dynamic adjustments to BESS pricing in response to hourly electricity rates, the system makes the best use of renewable energy during low-cost periods. Figure 4.12 shows the optimized total power received and returned from the grid as 141 kW, 4.06 kW, and the one-day cost as 9.25 $. It can be seen that the optimization reduces the total cost by 16% as shown in Table 4.1. In this case, the use of the BESS, EV with renewable resources and receiving power from the grid is highest at 9 AM is 14.5 kW and the lowest at 7 PM is 1.5 kW.

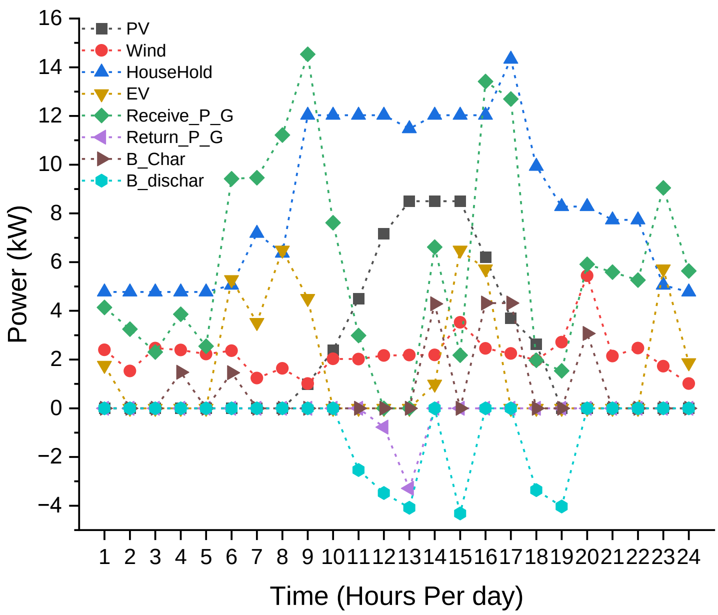

Figure 4. 12: Winter hourly power variation with House, EV load, and Grid import and return power with optimization

Table 4. 1: Winter case 2, with/without optimization and EV

Without EV		
	Without Optimization	With Optimization
Receive_P_G	113.3 kW	103.1 kW
Return_P_G	4.09 kW	8.3 kW
Per day cost	8.18 $	6.41 $
With EV		
Receive_P_G	152.7 kW	141.2 kW
Return_P_G	1.1 kW	4.0 kW
Per day cost	11.03 $	9.25 $

4.3.2.3 Case Study 3

$$P_{pv} + P_{wind} + P_{BESS} > Load \quad (4.3)$$

Through dynamic adjustments to BESS pricing in response to hourly electricity rates, the system makes the best use of renewable energy during low-cost periods. It stays off the grid during periods of high cost, as shown in Fig. 4.13. This strategy is to improve the operating conditions, together with a concurrent decrease in the cost of fuel, grid energy purchases, and CO_2 emissions.

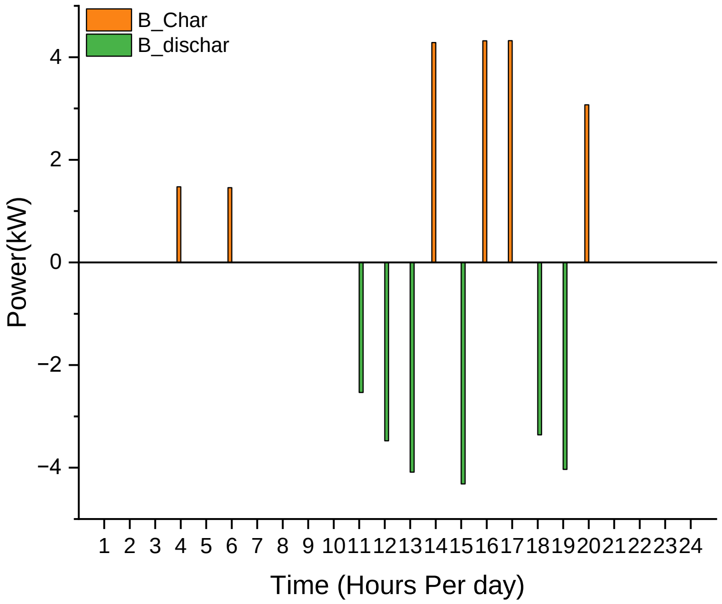

Figure 4. 13: Winter Charging and Discharging of BESS based on electricity price

Figure 4.14 describes the optimized time for EV charging based on cost and time. The method that is being provided shows how EV car charging may be optimized by carefully timing charging sessions to coincide with times when power is most affordable.

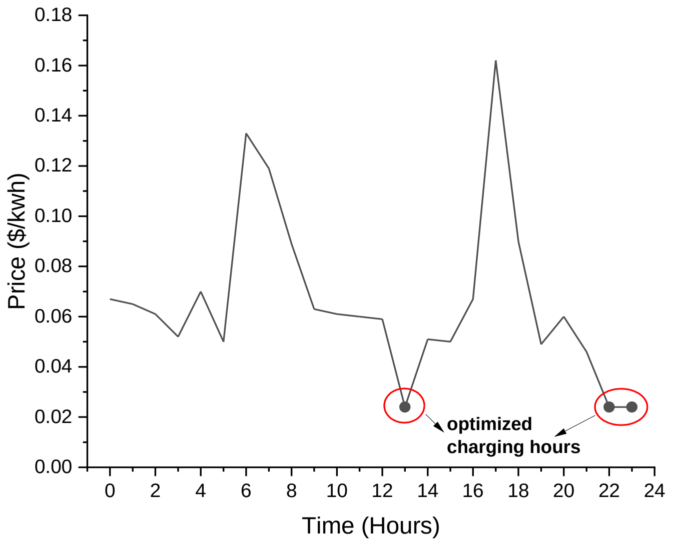

Figure 4. 14: Winter-optimized EV car charging time

In addition to guaranteeing economical energy use, this enhances the MG system's overall sustainability. Incorporating BESS is essential for reducing excessive power bills, improving energy use flexibility, bills, improving energy use flexibility, and encouraging eco-friendly EV charging habits.

4.3.2.4 Case Study 4 Proactive EV charging technique

A proactive EV charging system was used, which is an innovative technique for managing EV charging that optimizes energy use, lowers costs, and has a low effect on the power grid, unlike standard charging systems which allow EV owners to plug-in their vehicles to start charging instantly in this case EV charging cost is higher than to proactive case. Figure 4.15 shows the EV without considering the proactive algorithm, while Fig. 4.16 presents EV charging with implementing proactive algorithms.

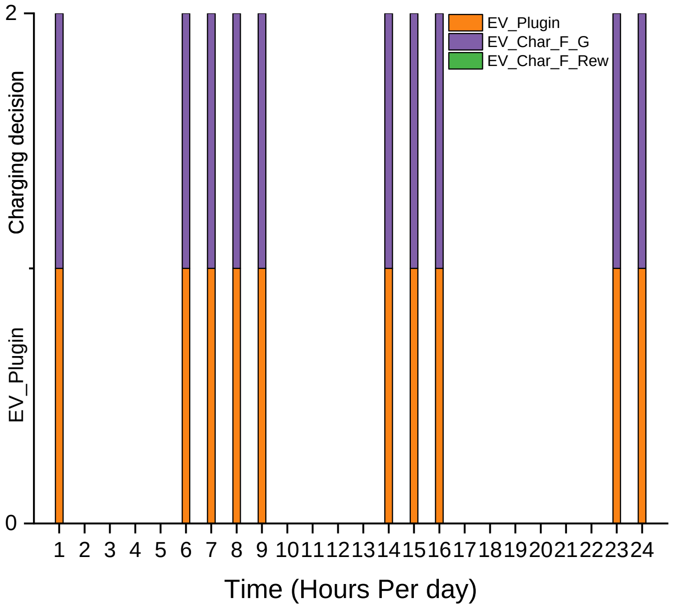

Figure 4. 15: Winter EV Charging without Proactive Optimization Algorithm

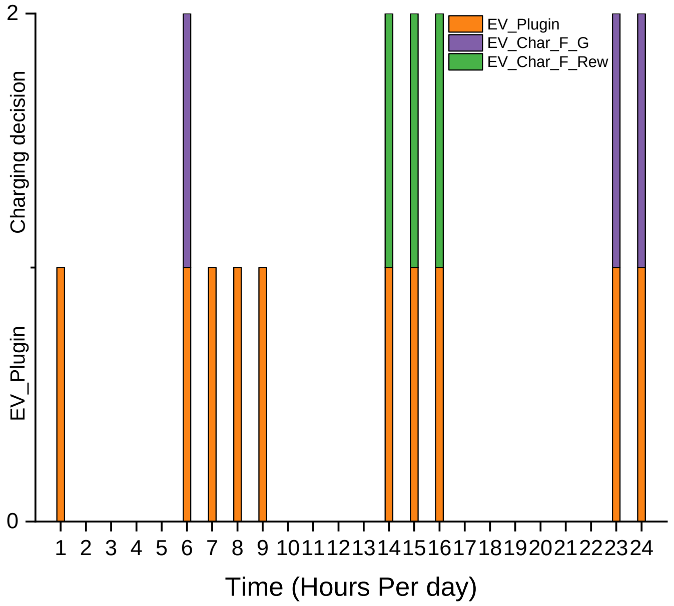

Figure 4. 16: Winter EV Charging with Proactive Optimization Algorithm

Proactive charging systems employ powerful algorithms and real-time data to intelligently manage and regulate the charging process. It can be seen in Fig 4.16 that the system checks the renewable energy and BESS charging if any is available, and then the EV charging by renewable and BESS. When renewable and BESS are unavailable, the system checks the electricity price, tries to charge the EV at the lowest cost, and optimizes the EV charging hours.

4.3.3 Spring season.

4.3.3.1 Case Study 1 (PV, Wind, and Grid)

The daily load curve shows a maximum power generation of 12 kW for the house and 6.6 kW for the EV. The load profile varies during the day and weather, with high demand from 8 AM to 4 PM and low demand at night. In this case, MG runs without BESS, WT, and the main grid supply power in the morning when energy prices are low, and PV is not available. Then, the PV system produces energy to satisfy the demand for housing load. At the same time, the power produced by the grid decreases, as shown in Fig. 4.17.

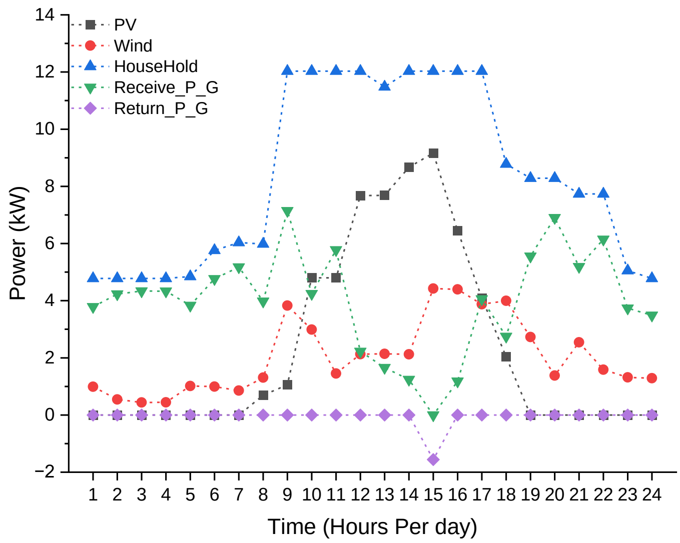

Figure 4. 17: Spring hourly power variation with House load and Grid import, return power

The grid works with the WT to supply electricity as PV production decreases. The energy demand is low at midnight WT's provide the power this time. All the energy needed to meet the electricity demand is obtained from the grid, resulting in extremely high purchasing costs. In this case, receiving power from the grid is highest at 9 AM is around 7.1 kW the lowest power at 3 PM is 0.0 kW, and return power to the grid at 3 PM is 1.5 kW.

Figure 4.18 shows after the EV load is added to the residential load, the amount of grid electricity imported rises. Because of the lack of storage devices, operating in this mode makes the system less economical outside of periods of renewable output when all demand is fulfilled by purchasing power from the grid (stationary BESS). In this scenario, receiving power from the grid is high at 9 a.m., about 12 kW, and the lowest power at 1 p.m. is 1.6 kW, with no return power to the grid since PV and WT power are insufficient.

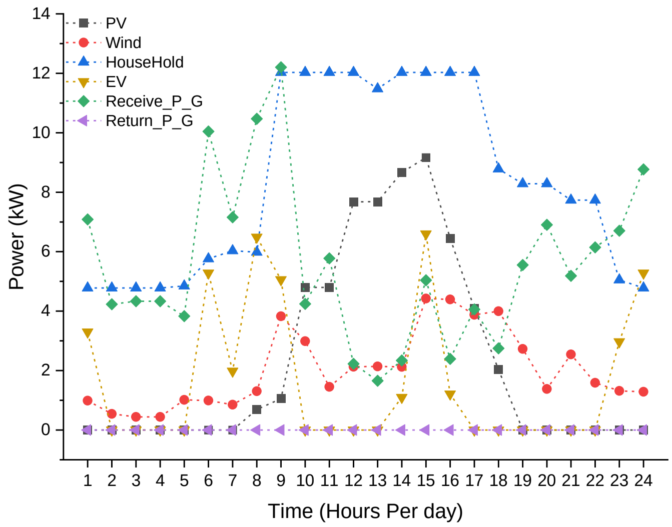

Figure 4. 18: Spring hourly power variation with House, EV load and Grid import, return power

4.3.3.2 Case Study 2 (PV, Wind, BESS, and Grid)

In another case study, to capitalize on cost-effective energy pricing, the grid and WT collaborate to satisfy demand and enable battery charging before dawn. This strategy aims to keep the SOC between 20% and 80%, with a minimum of SOC_{min} below 20%.

$$P_{pv} + P_{wind} > Load \tag{4.4}$$

$$P_{pv} + P_{wind} < Load \tag{4.5}$$

When more electricity is generated than used, PV and WT systems are utilized to satisfy demand, with a preference for using extra power from renewable sources. When BESS is not completely charged, extra energy is used to raise the SOC to its maximum limit at a fair cost. The remaining extra energy will be employed as a second priority, returning the electricity to the grid. Initially, the analysis was performed without implementing optimization techniques, as shown in Fig. 4.19. The total power received and returned can be noted as 105.3 kW and 3.9 kW, respectively. Additionally, per day cost was calculated (3.33 $ without optimization) as presented in Table 4.2.

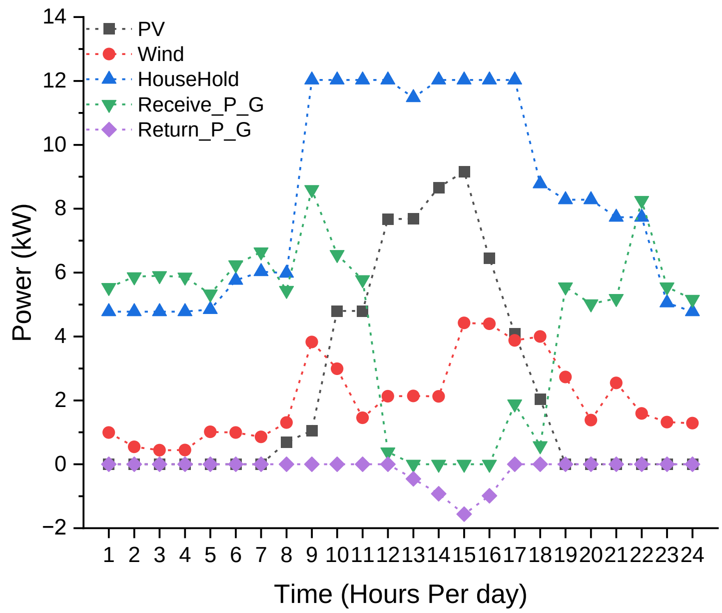

Figure 4. 19: Spring hourly power variation with House load, and Grid import, return power without optimization

Figure 4.20 shows the optimized power received and returned from the grid as 94.3 kW and 7.9 kW, respectively. The per-day cost for this case can be noted as 2.74 $. It can be observed that optimization results in a 17 % reduction in price. In this case, the use of the BESS with renewable resources and receiving power from the grid is highest at 5 PM is 8.3 kW and the lowest at 4 PM is 1.1 kW.

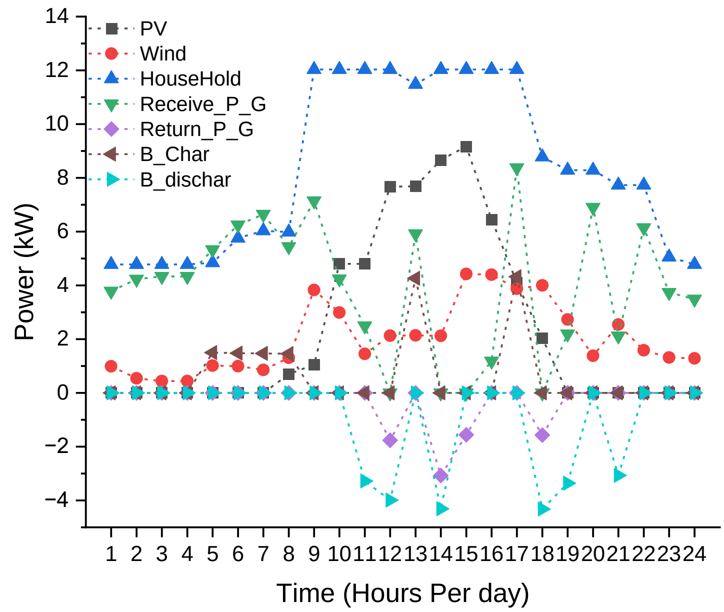

Figure 4. 20: Spring hourly power variation with House load, and Grid import, return power with optimization

If an EV is available without optimization, the total received power from the grid is 138.9 kW, the total returned power to the grid is 0.4 kW, and the day cost is 4.58 $, as shown in Fig. 4.21 and Table 4.2, respectively.

If an EV is available after charging the BESS, the remaining power is initially used to charge the EV battery, and if it remains in excess, it will be returned to the grid. The BESS begins to discharge to make up the power deficit when demand exceeds consumption. The BESS and the WT feed the load to its ultimate SOC_{min} limit.

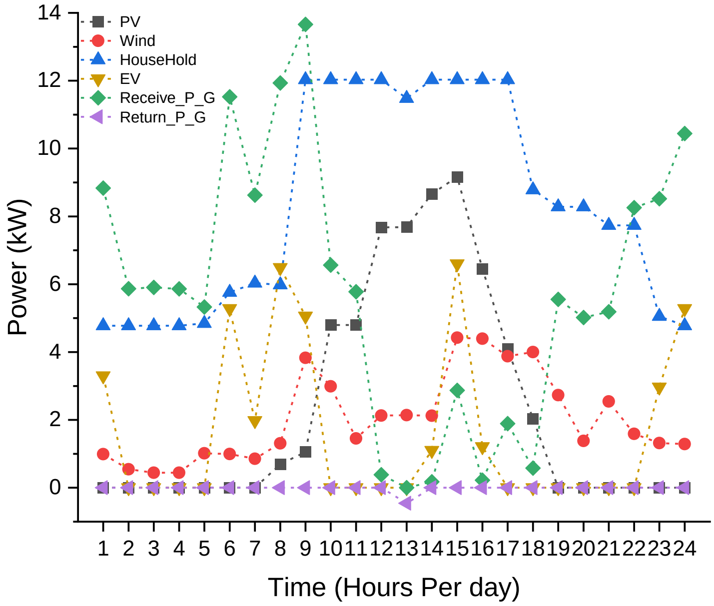

Figure 4. 21: Spring hourly power variation with House, EV load, and Grid import, return power without optimization

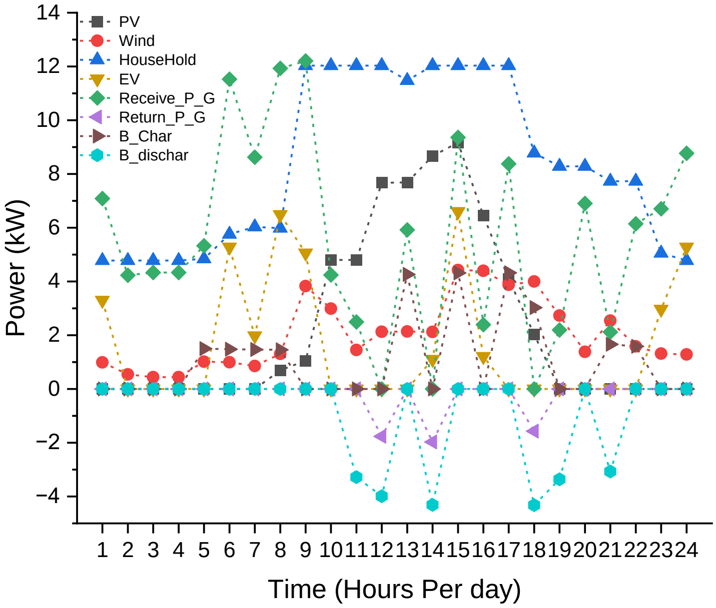

Figure 4. 22: Spring hourly power variation with House, EV load, and Grid import, return power with optimization

Using dynamic adjustments to BESS pricing in response to hourly electricity rates, the system makes the best use of renewable energy during low-cost periods. Fig. 4.22 shows the optimized total power received and returned from the grid as 135.2 kW, 5.3 kW, and the one-day cost as 4.21 $. It can be seen that the optimization reduces the total cost by 8% as shown in Table 4.2. Furthermore, the use of BESS, an EV with renewable resources, and receiving power from the grid is highest at 9 AM is 12.2 kW and the lowest at 9 PM is 2.1 kW.

Table 4. 2: Spring case 2, with/without optimization and EV

Without EV		
	Without Optimization	With Optimization
Receive_P_G	105.3 kW	94.3 kW
Return_P_G	3.9 kW	7.9 kW
Per day cost	3.33 $	2.74 $
With EV		
Receive_P_G	138.9 kW	135.2 kW
Return_P_G	0.4 kW	5.3 kW
Per day cost	4.58 $	4.21 $

4.3.3.3 Case Study 3

$$P_{pv} + P_{wind} + P_{BESS} > Load \tag{4.6}$$

The system optimizes renewable energy consumption during low-cost periods by dynamically adjusting BESS pricing in response to hourly power costs. It stays off the grid during high-cost times, as seen in Fig. 4.23. This technique aims to enhance operational conditions while decreasing fuel costs, grid energy purchases, and CO2 emissions.

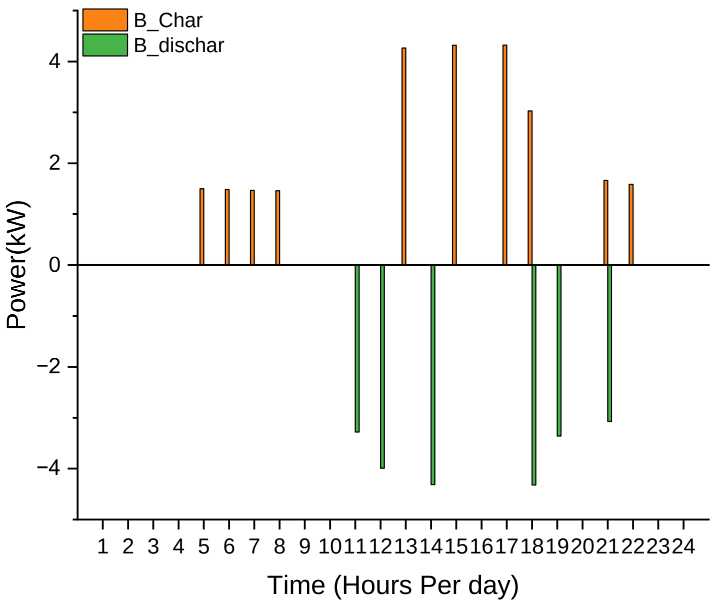

Figure 4. 23: Spring Charging and discharging of BESS based on electricity price

Figure 4.24 depicts the optimal timing for EV charging in terms of cost and time. The strategy described here demonstrates how EV car charging may be optimized by carefully arranging charging hours to coincide with periods when power is most inexpensive. This not only ensures efficient energy consumption but also improves the overall sustainability of the MG system. Incorporating BESS is critical for lowering high power costs, increasing energy usage flexibility, and encouraging environmentally beneficial EV charging behaviors.

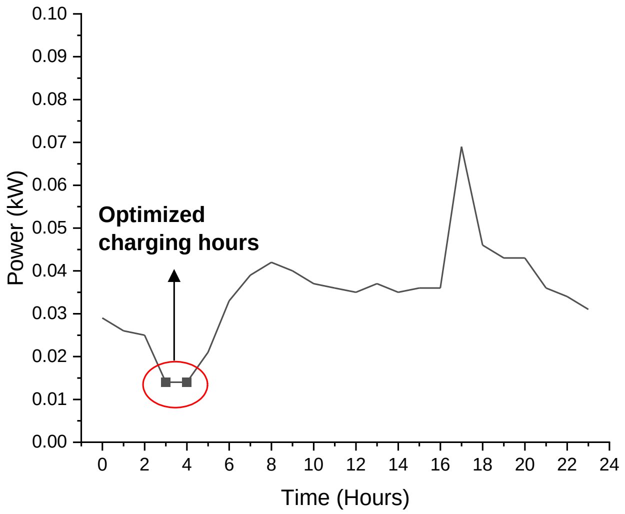

Figure 4. 24: Spring-optimized EV car charging time

4.3.3.4 Case Study 4 Proactive EV charging technique

A proactive EV charging system was used, which is an innovative technique for managing electric car charging that optimizes energy use, lowers costs, and has a low impact on the power grid.

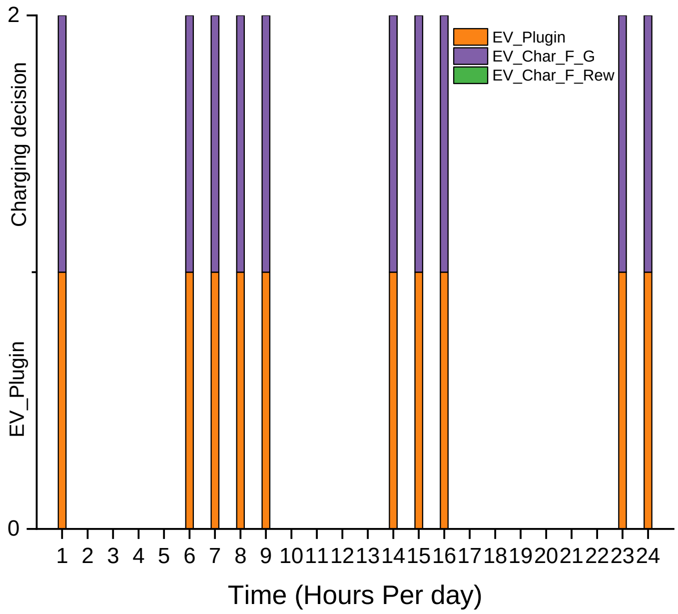

Figure 4. 25: Spring EV Charging without Proactive Optimization Algorithm

Unlike standard charging systems, which allow EV owners to plug in their vehicles and start charging immediately, the cost of EV charging is higher than the proactive case. Figure 4.25 shows the EV without considering the proactive algorithm, while Fig. 4.26 presents EV charging with implementing proactive algorithms.

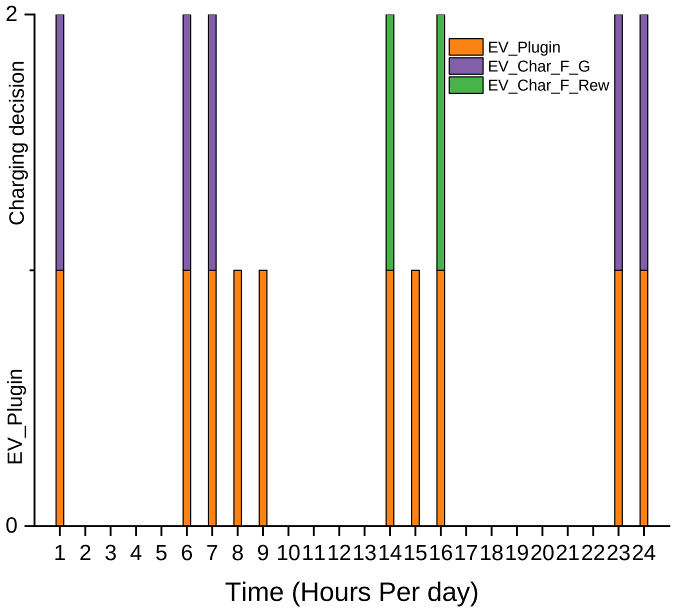

Figure 4. 26: Spring EV Charging with Proactive Optimization Algorithm

Proactive charging systems use advanced algorithms and real-time data to automatically control and regulate the charging process. Figure 4.26 shows that the system first checks for renewable energy and BESS charging, if any are available, before charging the EV using renewable and BESS. When renewable and BESS are unavailable, the system examines the energy market, attempts to charge the EV at the lowest possible cost, and optimizes the EV charging hours.

4.3.4 Autumn season.

4.3.4.1 Case Study 1 (PV, Wind, and Grid)

The daily load curve shows a maximum power generation of 14.6 kW for the house and 6.1 kW for the EV. The load profile varies during the day and weather, with high demand from 7 AM to 6 PM and low demand at night.

In this case, MG runs without BESS, WT, and the main grid supply power in the morning when energy prices are low, and PV is not available. Then, the PV system produces energy to satisfy the demand for housing load. At the same time, the power produced by the grid decreases, as shown in Fig. 4.27. The grid works with the WT to supply electricity as PV production decreases. The energy demand is low at midnight WT's provide the power this time. All the energy needed to meet the electricity demand is obtained from the grid, resulting in extremely high purchasing costs. In this case, receiving power from the grid is highest at 8 AM is around 8.1 kW and the lowest power at 12 PM is 1.2 kW, and no return power to the grid since PV and WT power are insufficient.

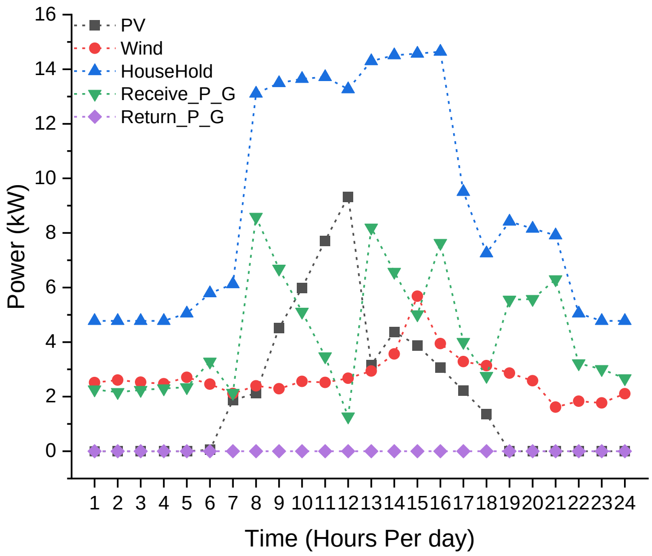

Figure 4. 27: Autumn hourly power variation with House load and Grid import, return power

Figure 4.28 shows after the EV load is added to the residential load, the amount of grid electricity imported rises. Because of the lack of storage devices, operating in this mode makes the system less economical outside of periods of renewable output when all demand is fulfilled by purchasing power from the grid (stationary BESS). In this scenario, receiving power from the grid is high at 8 AM, about 13 kW, and the lowest power at 12 PM is 1.2 kW, with no return power to the grid since PV and WT power are insufficient.

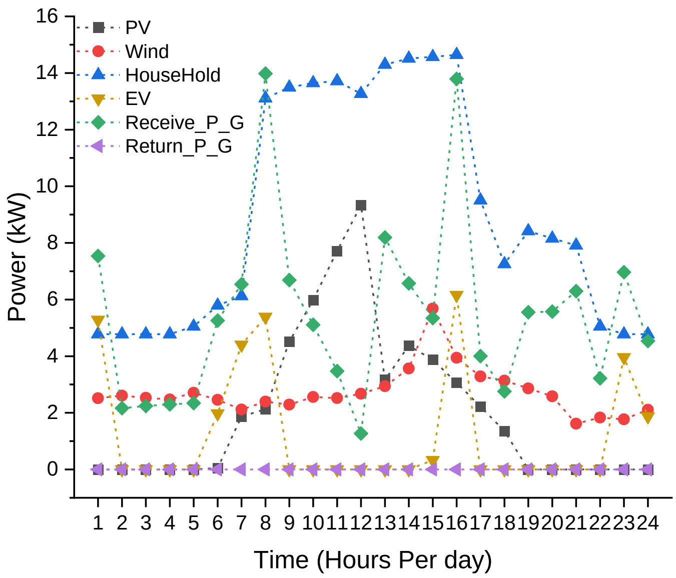

Figure 4. 28: Autumn hourly power variation with House load and Grid import, return power

4.3.4.2 Case Study 2 (PV, Wind, BESS, and Grid)

In another case study, to capitalize on cost-effective energy pricing, the grid and WT collaborate to satisfy demand and enable battery charging before dawn. This strategy aims to keep the SOC between 20% and 80%, with a minimum of SOC_{min} below 20%.

$$P_{pv} + P_{wind} > Load \tag{4.7}$$

$$P_{pv} + P_{wind} < Load \tag{4.8}$$

When more electricity is generated than used, PV and WT systems are utilized to satisfy demand, with a preference for using extra power from renewable sources. When BESS is not completely charged, extra energy is used to raise the SOC to its maximum limit at a fair cost. The remaining extra energy will be employed as a second priority: to restore electricity to the grid. Initially, the analysis was performed without implementing optimization techniques, as shown in Fig. 4.29. The total power received and returned can be noted as 114.1 kW and 0.7 kW, respectively. Additionally, per day cost was calculated (5.38 $ without optimization) as presented in Table 4.3.

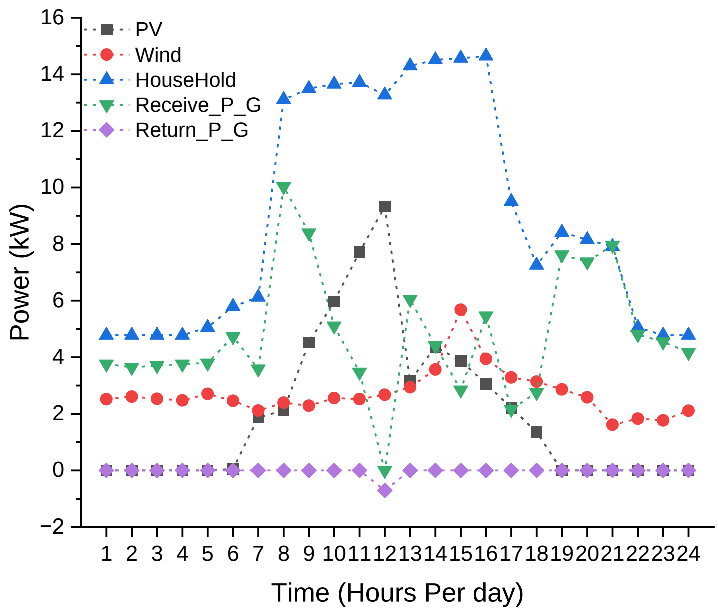

Figure 4. 29: Autumn hourly power variation with House load and Grid import, return power without optimization

Figure 4.30 shows the optimized power received and returned from the grid as 103.3 kW and 0.09 kW, respectively. The per-day cost for this case can be noted as 4.7 $. It can be observed that optimization results in a 12 % reduction in price. In this case, the use of the BESS with renewable resources and receiving power from the grid is highest at 8 AM is 8.5 kW and the lowest at 3 PM is 0.69 kW.

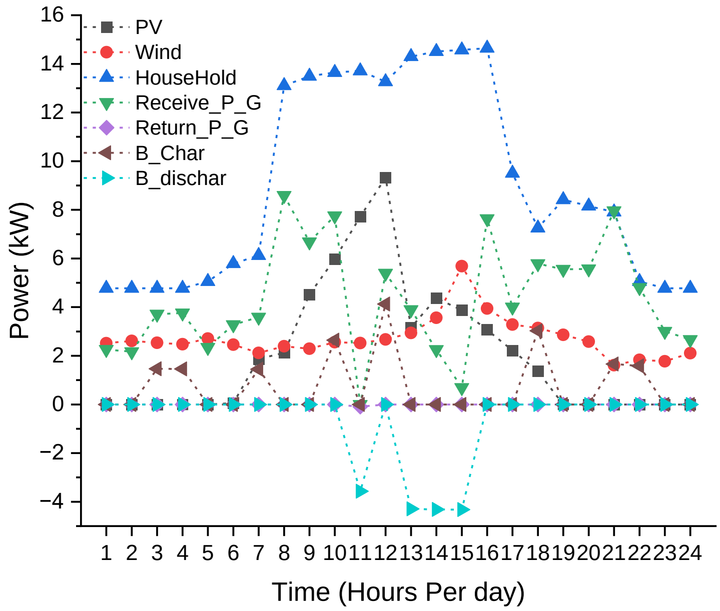

Figure 4. 30: Autumn hourly power variation with House load and Grid import, return power with optimization

If an EV is available without optimization, the total received power from the grid is 143.5 kW, the total returned power to the grid is 0.7 kW, and the day cost is 6.61 $, as shown in Fig. 4.31 and Table 4.3, respectively.

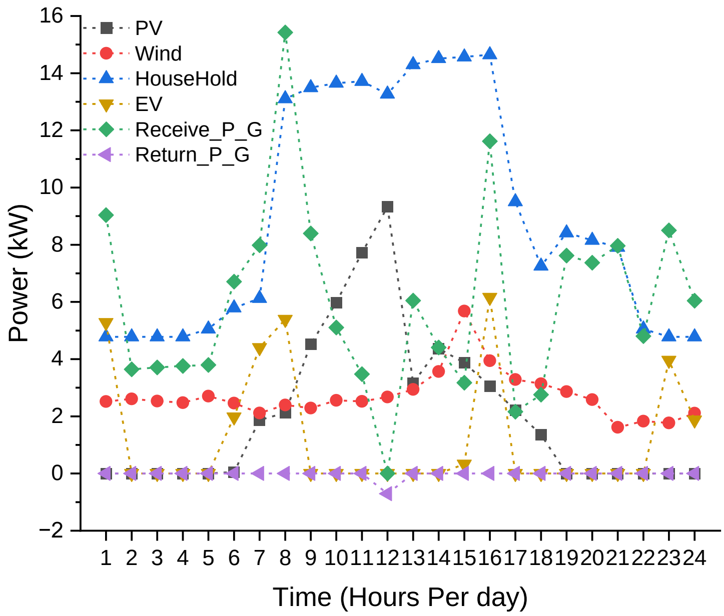

Figure 4. 31: Autumn hourly power variation with House, EV load and Grid import, return power without optimization

If an EV is available after charging the BESS, the remaining power is initially used to charge the EV battery, and if it remains in excess, it will be returned to the grid.

The BESS begins to discharge to make up the power deficit when demand exceeds consumption. The BESS and the WT feed the load to its ultimate SOC_{min} limit. Using dynamic adjustments to BESS pricing in response to hourly electricity rates, the system makes the best use of renewable energy during low-cost periods. Figure 4.32 shows the optimized total power received and returned from the grid as 132.7 kW, 0.09 kW, and the one-day cost as 6.01 $. It can be seen that the optimization reduces the total cost by 9% as shown in Table 4.3. Furthermore, the use of BESS, an EV with renewable resources, and receiving power from the grid is highest at 8 AM is 13.9 kW and the lowest at 3 PM is 1.02 kW.

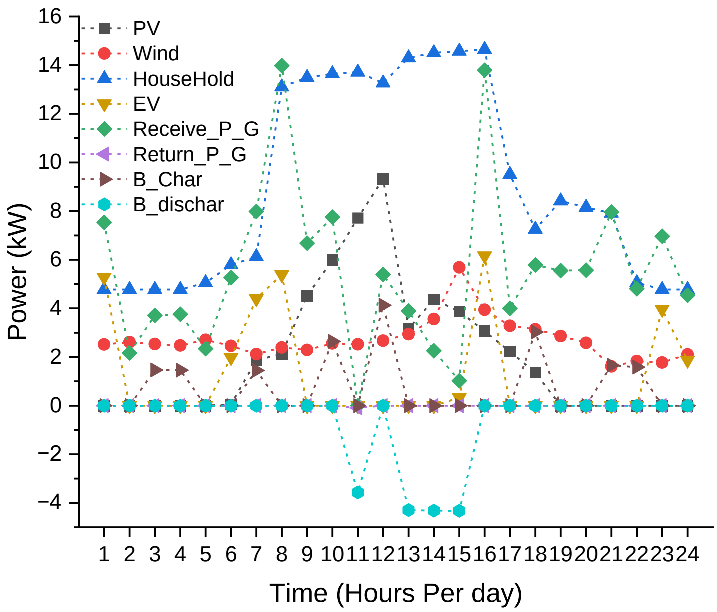

Figure 4. 32: Autumn hourly power variation with House, EV load, and Grid import, return power with optimization

Table 4. 3: Autumn case 2, with/without optimization and EV

Without EV		
	Without Optimization	With Optimization
Receive_P_G	114.1 kW	103.3 kW
Return_P_G	0.7 kW	0.09 kW
Per day cost	5.38 $	4.7 $
With EV		
Receive_P_G	143.5 kW	132.7 kW
Return_P_G	0.7 kW	0.09 kW
Per day cost	6.61 $	6.01 $

4.3.4.3 Case Study 3

$$P_{pv} + P_{wind} + P_{BESS} > Load \quad (4.9)$$

The system optimizes renewable energy consumption during low-cost periods by dynamically adjusting BESS pricing in response to hourly power costs. It stays off the grid during high-cost times, as seen in Fig. 4.33. This technique aims to enhance operational conditions while decreasing fuel costs, grid energy purchases, and CO2 emissions.

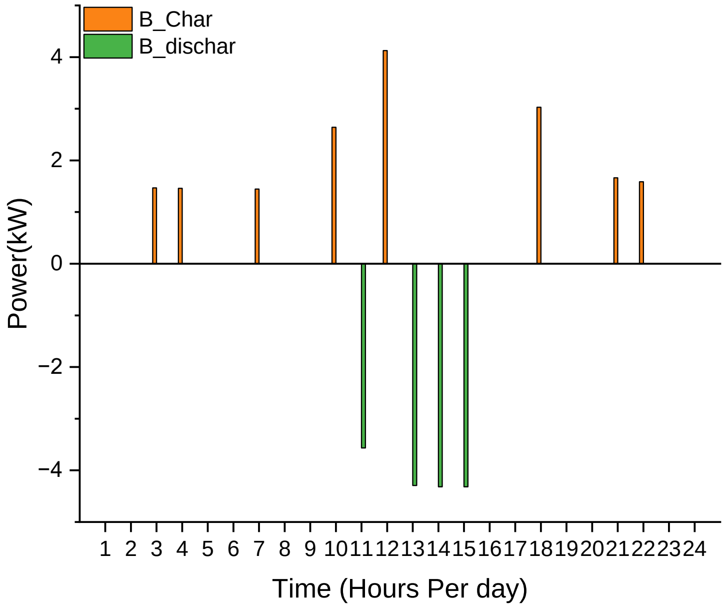

Figure 4. 33: Autumn charging and discharging of BESS based on electricity price

Figure 4.34 depicts the optimal timing for EV charging in terms of cost and time. The strategy described here demonstrates how EV car charging may be optimized by carefully arranging charging hours to coincide with periods when power is most inexpensive.

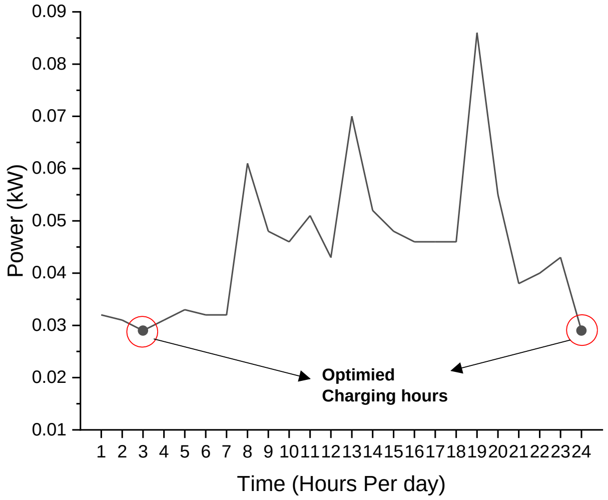

Figure 4. 34: Autumn-optimized EV car charging time

This not only ensures efficient energy consumption but also improves the overall sustainability of the MG system. Incorporating BESS is critical for lowering high power costs, increasing energy usage flexibility, and encouraging environmentally beneficial EV charging behaviors.

4.3.4.4 Case Study 4 Proactive EV charging technique

A proactive EV charging system was used, which is an innovative technique for managing EV charging that optimizes energy use, lowers costs, and has a low impact on the power grid. Unlike standard charging systems, which allow EV owners to plug in their vehicles and start charging immediately, the cost of EV charging is higher than to the proactive case. Figure 4.35 shows the EV without considering the proactive algorithm, while Fig. 4.36 presents EV charging with implementing proactive algorithms.

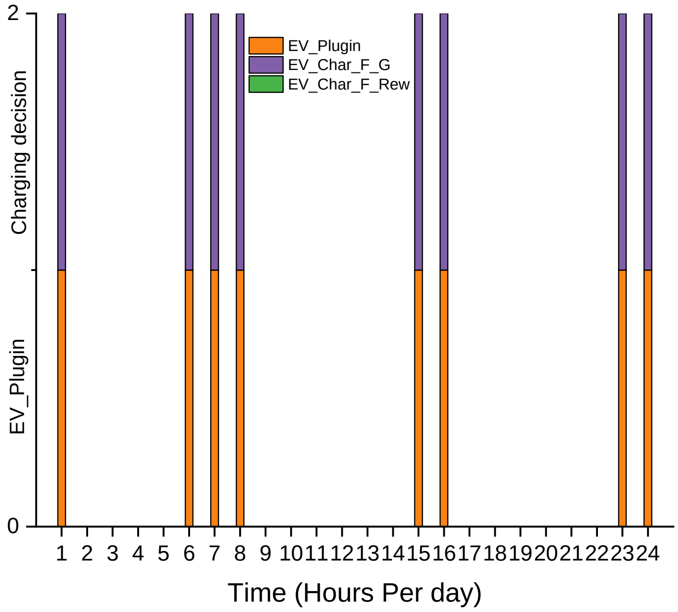

Figure 4. 35: Autumn EV Charging without Proactive Optimization Algorithm

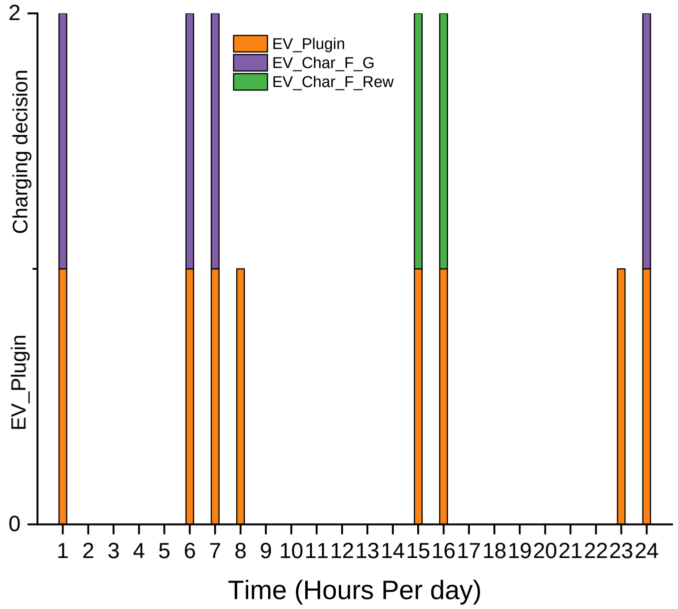

Figure 4. 36: Autumn EV Charging with Proactive Optimization Algorithm

Proactive charging systems use advanced algorithms and real-time data to automatically control and regulate the charging process. Figure 4.36 shows that the system first checks for renewable energy and BESS charging, if any are available, before charging the EV using renewable and BESS. When renewable and BESS are unavailable, the system examines the energy market, attempts to charge the EV at the lowest possible cost, and optimizes the EV charging hours, resulting in a 54% cost savings.

4.3.5 Summer season.

4.3.5.1 Case Study 1 (PV, Wind, and Grid)

The daily load curve shows a maximum power generation of 15.7 kW for the house and 6.4 kW for the electric car. The load profile varies during the day and weather, with high demand from 7 AM to 5 PM and low demand at night.

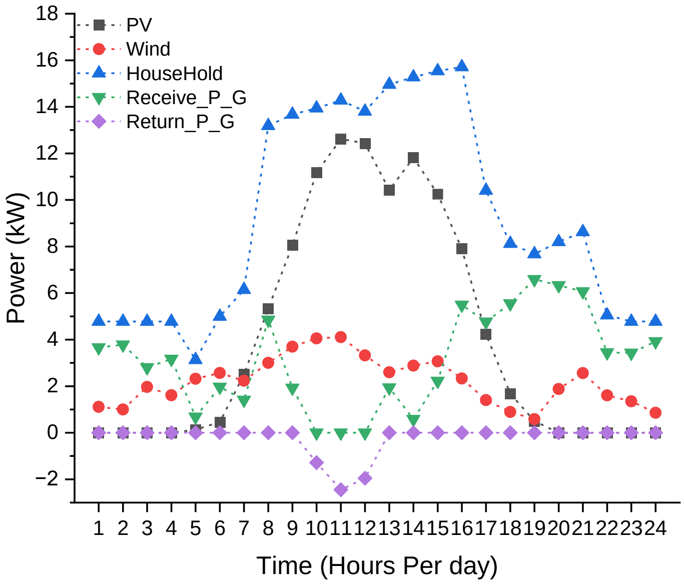

Figure 4. 37: Summer hourly power variation with House load and Grid import, return power

In this case, MG runs without BESS, WT's, and the main grid supply power in the morning when energy prices are low, and PV is not available. Then, the PV system produces energy to satisfy the demand for housing load. At the same time, the power produced by the grid decreases, as shown in Fig. 4.37. The grid works with the WT to supply electricity as PV production decreases. The energy demand is low at midnight WT provides the power this time. All the energy needed to meet the electricity demand is obtained from the grid, resulting in extremely high purchasing costs. In this case, receiving power from the grid is highest at 8 AM is 4.8 kW, and from 10 AM to 12 AM no power is received from the grid, and return power to the grid from 10 to 12 AM is a total of 5.67 kW. Figure 4.38 shows after the EV load is added to the residential load, the amount of grid electricity imported rises. Because of the lack of storage devices, operating in this mode makes the system less economical outside of periods of renewable output when all demand is fulfilled by purchasing power from the grid (stationary BESS). In this scenario, receiving power from the grid is highest at 8 AM is 11 kW, and from 10 AM to 12 AM no power is received from the grid, and return power to the grid from 10 to 12 AM is a total of 5.67 kW.

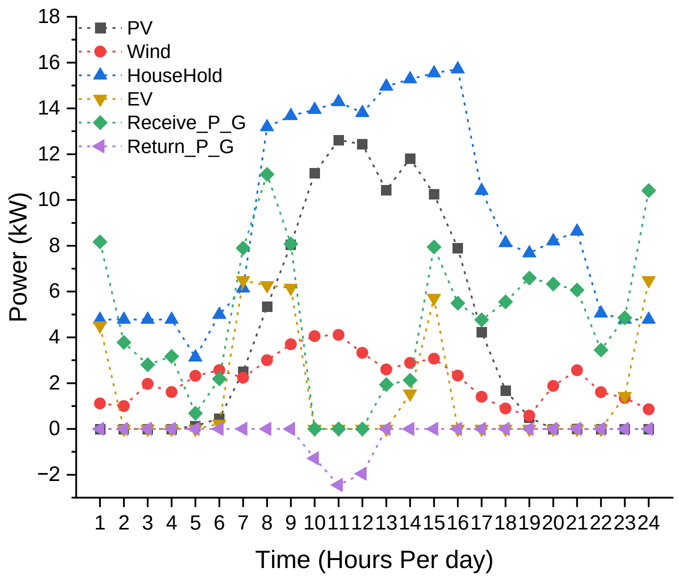

Figure 4. 38: Summer hourly power variation with House, EV load and Grid import, return power

4.3.5.2 Case Study 2 (PV, Wind, BESS, and Grid)

In another case study, to capitalize on cost-effective energy pricing, the grid and WT collaborate to satisfy demand and enable battery charging before dawn. This strategy aims to keep the SOC between 20% and 80%, with a minimum of SOC_{min} below 20%.

$$P_{pv} + P_{wind} > Load \tag{4.10}$$

$$P_{pv} + P_{wind} < Load \tag{4.11}$$

When more electricity is generated than used, PV and WT systems are utilized to satisfy demand, with a preference for using extra power from renewable sources. When the BESS is not completely charged, extra energy is used to raise the SOC to its maximum limit at a fair cost. The remaining extra energy will be employed as a second priority: to restore electricity to the grid. Initially, the analysis was performed without implementing optimization techniques, as shown in Fig. 4.39. The total power received and returned can be noted as 88.01 kW and 6.2 kW, respectively. Additionally, per day cost was calculated (6.69 $ without optimization) as presented in Table 4.4.

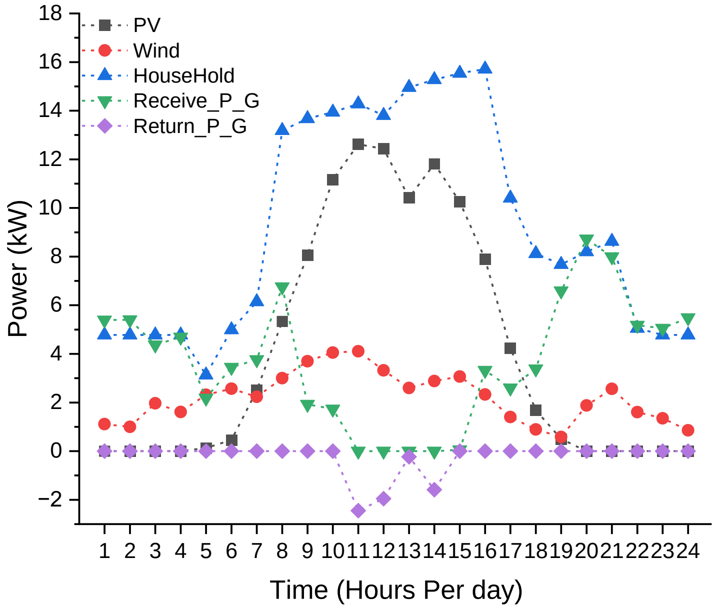

Figure 4. 39: Summer hourly power variation with House load and Grid import, return power without optimization

Figure 4.40 shows the optimized power received and returned from the grid as 75.1 kW and 8.1 kW, respectively. The per-day cost for this case can be noted as 5.2 $. It can be observed that optimization results in a 21 % reduction in price. In this case, the use of the BESS with renewable resources and receiving power from the grid is highest at 9 PM is 7.9 kW, and the lowest at 5 PM is 0.44 kW.

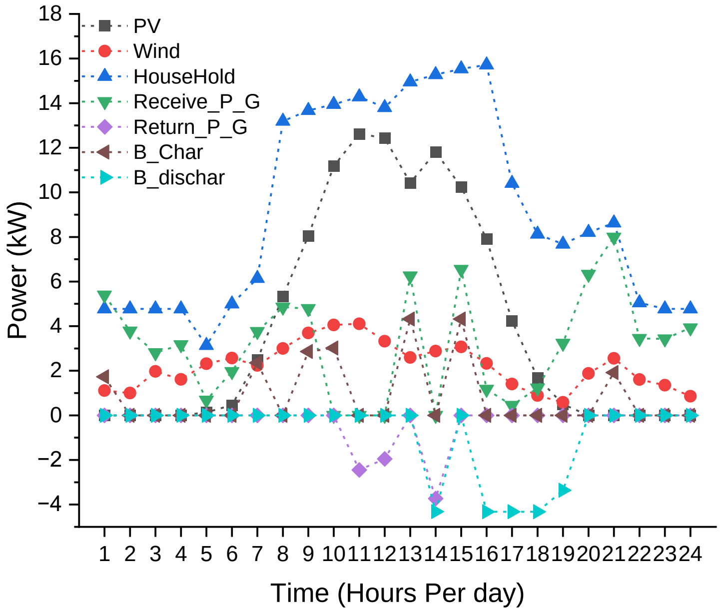

Figure 4. 40: Summer hourly power variation with House load and Grid import, return power with optimization

If an EV is available without optimization, the total received power from the grid is 125.3 kW, the total returned power to the grid is 4.6 kW, and the day cost is 9.82 $, as shown in Fig. 4.41 and Table

4.4, respectively.

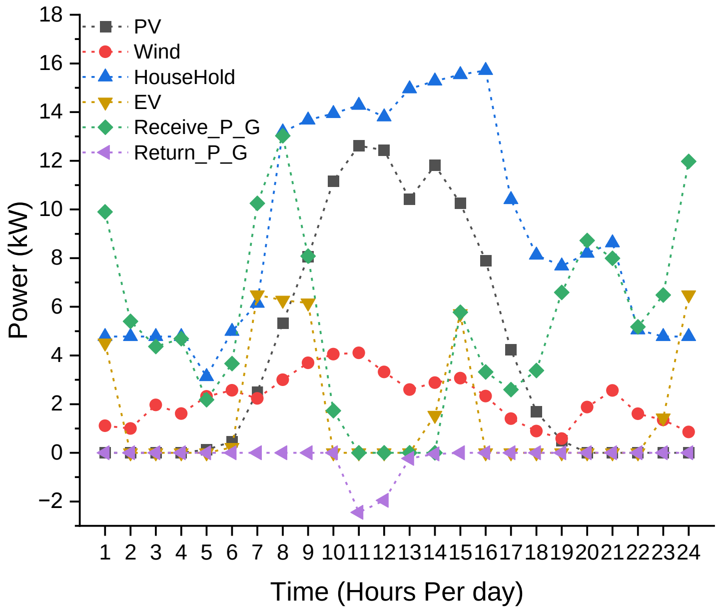

Figure 4. 41: Summer hourly power variation with House, EV load, and Grid import, return power without optimization

If an EV is available after charging the BESS, the remaining power is initially used to charge the EV battery, and if it remains in excess, it will be returned to the grid.

The BESS begins to discharge to make up the power deficit when demand exceeds consumption. The BESS and the WT feed the load to its ultimate SOC_{min} limit. Using dynamic adjustments to BESS pricing in response to hourly electricity rates, the system makes the best use of renewable energy during low-cost periods. Fig. 4.42 shows the optimized total power received and returned from the

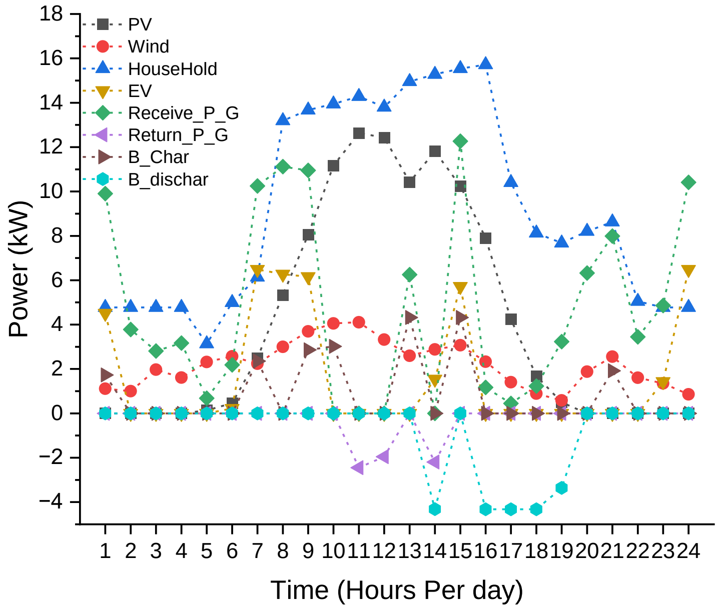

Figure 4. 42: Summer hourly power variation with House, EV load and Grid import, return power with optimization

grid as 112.4 kW, 6.5 kW, and the one-day cost as 8.38 $. It can be seen that the optimization reduces the total cost by 14% as shown in Table 4.4. Furthermore, the use of BESS with renewable resources and receiving power from the grid is highest at 3 PM is 12.2 kW and the lowest at 5 PM is 0.44 kW.

Table 4. 4: Summer case 2, with/without optimization and EV

Without EV		
	Without Optimization	With Optimization
Receive_P_G	88.01 kW	75.1 kW
Return_P_G	6.2 kW	8.1 kW
Per day cost	6.69 $	5.25 $
With EV		
Receive_P_G	125.3 kW	112.4 kW
Return_P_G	4.67 kW	6.51 kW
Per day cost	9.82 $	8.38 $

4.3.5.3 Case Study 3

$$P_{pv} + P_{wind} + P_{BESS} > Load \quad (4.12)$$

The system optimizes renewable energy consumption during low-cost periods by dynamically adjusting BESS pricing in response to hourly power costs. It stays off the grid during high-cost times, as seen in Fig. 4.43. This technique aims to enhance operational conditions while decreasing fuel costs, grid energy purchases, and CO2 emissions.

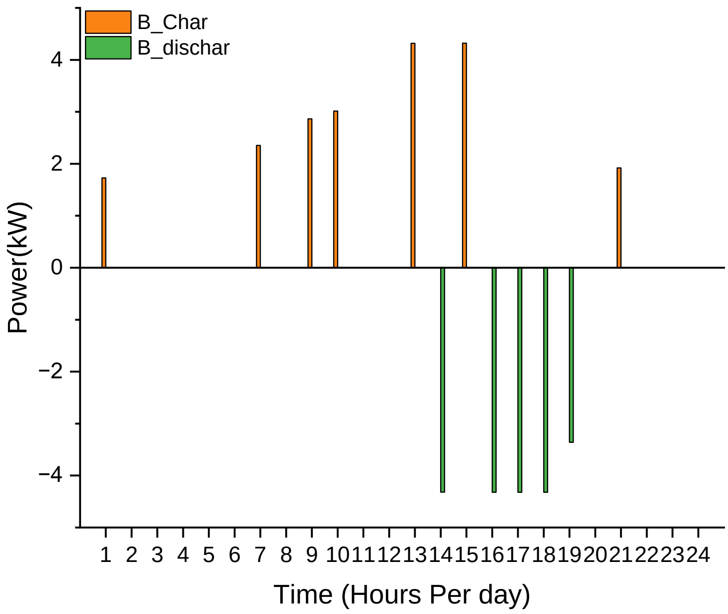

Figure 4. 43: Summer charging and discharging of BESS based on electricity price

Figure 4.44 depicts the optimal timing for EV charging in terms of cost and time. The strategy described here demonstrates how EV car charging may be optimized by carefully arranging charging hours to coincide with periods when power is most inexpensive. This not only ensures efficient energy consumption but also improves the overall sustainability of the MG system. Incorporating BESS is critical for lowering high power costs, increasing energy usage flexibility, and encouraging environmentally beneficial EV charging behaviors.

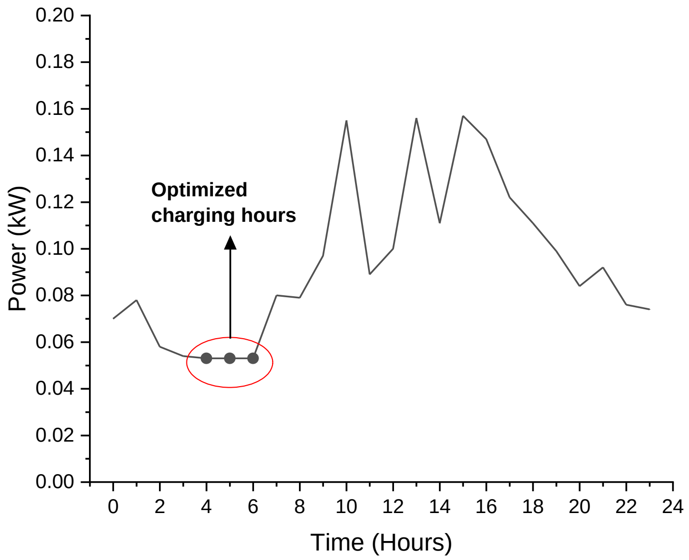

Figure 4. 44: Summer-optimized EV car charging time

4.3.5.4 Case Study 4 Proactive EV charging technique

A proactive EV charging system was used, which is an innovative technique for managing EV charging that optimizes energy use, lowers costs, and has a low impact on the power grid. Unlike standard charging systems, which allow EV owners to plug in their vehicles and start charging

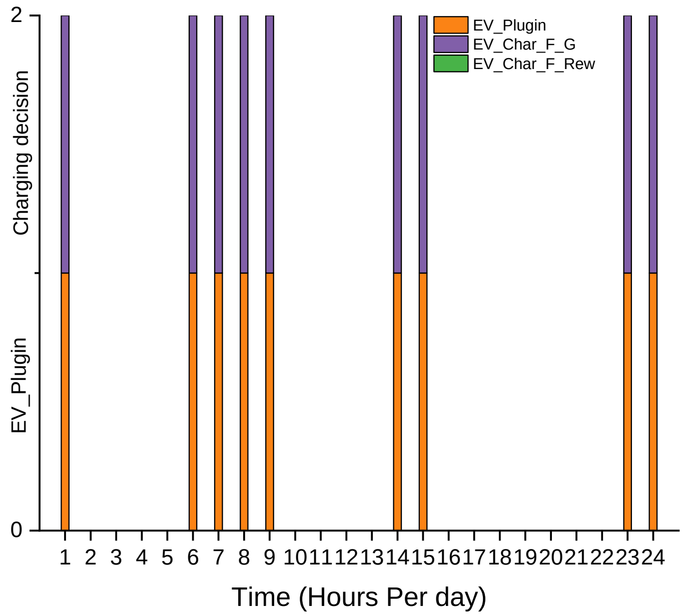

Figure 4. 45: Summer EV Charging without Proactive Optimization Algorithm

immediately, the cost of EV charging is higher than the proactive case. Figure 4.45 shows the EV without considering the proactive algorithm, while Fig. 4.46 presents EV charging with implementing proactive algorithms.

Proactive charging systems use advanced algorithms and real-time data to automatically control and regulate the charging process. Figure 4.46 shows that the system first checks for renewable energy and BESS charging, if any are available, before charging the EV using renewable and BESS. When renewable and BESS are unavailable, the system examines the energy market, attempts to charge the EV at the lowest possible cost, and optimizes the EV charging hours, resulting in a 48% cost savings.

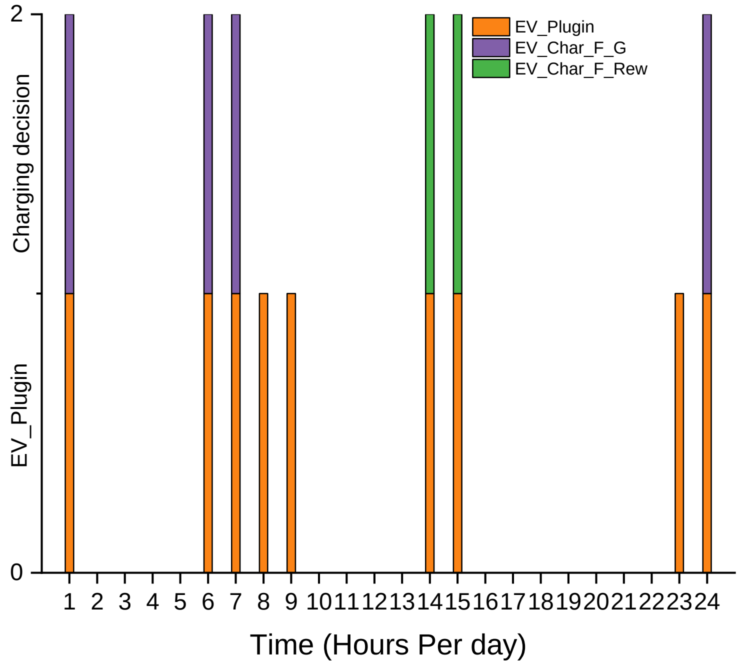

Figure 4. 46: Summer EV Charging with Proactive Optimization Algorithm

4.4 Discussion

This study considered multiple case studies while using the PSO as an optimization technique to create the best scheduling mode for EV car charging, aiming to produce a more optimized EMS. The suggested MG EMS, which integrates RESs, including PV, WT, BESS, EV, and the main grid, is evaluated using a MATLAB algorithm simulation. Several scenarios are implemented to see how the EMS behaves in power-sharing across various sources in all operational modes (electricity pricing, BESS SOC, house load, and EV charging time frames). For this simulation, 24 hours are considered to test the different scenarios. In all case studies, the SOC_{min} and SOC_{max} are 20% and 80%, respectively. Depending on the amount of sun irradiation, the solar system operates in all modes with a regular distribution over the day, peaking in power at noon. Throughout the day, there are peaks and troughs in the wind generation due to the wind speed, which varies randomly. The PSO algorithm applies to all seasons and analyzes the optimized power every season.

In winter, 14 kW is the maximum house load, while 6 kW of EV load is observed. In the first case, the optimized receiving power from the grid without an EV is 10 kW, and with an EV is 15 kW. When BESS is connected to the system with optimization, without EV load, the total optimized receiving power from the grid is 103.1 kW, the total optimized return power is 8.3 kW, and the cost saving is 21%; with EV, the total optimized receiving power from the grid is 141.2 kW, the total optimized return power is 4.05 kW, and the cost saving is 16 %. Without optimization, without EV load, the total optimized receiving power from the grid is 113.3 kW, and the total optimized return power is 4.09 kW; with EV, the total optimized receiving power from the grid is 152.7 kW, the total optimized return power is 1.13 kW, and as well as save the 80% cost using proactive EV charging technique.

In spring, 12 kW is the maximum house load, and 6.6 kW is the EV load. In the first case, the highest optimized receiving power from the grid without an EV is 7.1 kW, and the total optimized return power to the grid is 1.5 kW, and with an EV is 12 kW. When BESS is connected to the system without EV load, the total optimized receiving power from the grid is 94.3 kW, the total optimized return power is 7.9 kW, and the cost saving is 17 %; with EV, the total optimized receiving power from the grid is 135.2 kW, the total optimized return power is 5.3 kW, and the cost saving is 8%. Without optimization, without EV load, the total optimized receiving power from the grid is 105.3 kW, and the total optimized return power is 3.92 kW; with EV, the total optimized receiving power from the grid is 138.9 kW, the total optimized return power is 0.45 kW, and as well as save the 47% cost using proactive EV charging technique.

In autumn, 14.6 kW is the maximum house load, and 6.1 kW is the EV load. In the first case, the highest optimized receiving power from the grid without an EV is 8.1 kW, and with an EV is 13 kW. When BESS is connected to the system without EV load, the total optimized receiving power from the grid is 103.3 kW, the total optimized return power is 0.09 kW, and the cost saving is 12 %; with EV, the total optimized receiving power from the grid is 132.7 kW, the total optimized return power is 0.09 kW, and the cost saving is 9 %. Without optimization, without EV load, the total optimized receiving power from the grid is 114.1 kW, and the total optimized return power is 0.70 kW; with EV, the total optimized receiving power from the grid is 143.5 kW, the total optimized return power is 0.70 kW, and as well as save the 54% cost using proactive EV charging technique.

In summer, 15.7 kW is the maximum house load, and 6.4 kW is the EV load. In the first case, the highest optimized receiving power from the grid without an EV is 4.8 kW, the total optimized return power is 5.6 kW, with an EV is 11 kW, and the total optimized return power is 5.6 kW. When BESS is connected to the system without EV load, the total optimized receiving power from the grid is 75.1 kW, the total optimized return power is 8.1 kW, and the cost saving is 21 %; with EV, the total optimized receiving power from the grid is 112.4 kW, the total optimized return power is 6.5 kW, and the cost saving is 14 %. Without optimization, without EV load, the total optimized receiving power from the grid is 88.01 kW, and the total optimized return power is 6.2 kW; with EV, the total optimized receiving power from the grid is 125.3 kW, the total optimized return power is 4.67 kW, and as well as save the 48% cost using proactive EV charging technique.

Chapter 5 - Conclusion and Future Work

This thesis proposed an EMS in a grid connected to an MG that consists of EVs with variable loads, a PV system, a WT, and a BESS. PSO optimization technique has been developed to determine the best configuration of energy sources to minimize operating costs and grid dependence while maximizing renewable energy and electricity exchange. The demand and energy generation profiles are modeled and used as MG inputs for analyzing 16 scenarios with four seasons. Moreover, to assess the effects of battery on price optimization, a commercial battery, namely lithium-ion is employed in the proposed model. The simulation's findings showed the system's ability to generate electricity during varying times, following the power system's demands, and offering a more adaptable and effective service. Additionally, the energy exchange mechanism between the load and various sources illustrates the effectiveness of smart grids in maximizing energy exchanges with the main grid, optimizing the use of renewable resources, and improving energy management and consumption prices. The suggested scheduling technique lowers the energy cost of EVs. The scheduling problem was solved using PSO, with certain modifications based on the condition that if the electricity prices are low, batteries will be charged, and at higher prices, they will be discharged. Overall, the use of PSO in the proposed EMS for EV charging and battery charging/discharging is based on electricity price. Moreover, the results show that the implementation of PSO-based optimization results in a cost reduction of 21% and 16% in winter, 17% and 8% in spring, 12% and 9% in autumn, 21% and 14% in summer with and without EV consideration, respectively. These findings highlight the effectiveness of the PSO optimization technique in efficiently adjusting to various energy demand patterns. Significantly, the highest power consumption of the house in the summer was limited to 15.7 kW, whilst the lowest consumption in the spring was measured at 12 kW. In the same way, the EV load reached a peak of 6.4 kW during the summer and dropped to a minimum of 6 kW during the winter. In addition, the greatest total optimized electricity received from the grid during winter was 141.2 kW with EV, and during summer was 75.1 kW. As well as the greatest total optimized returned power to the grid during summer was 6.5 kW with EV, and during winter was 8.3 kW. The simulation results validate the approach and method. However, it is recommended that the reliability of this thesis be enhanced by implementing comparative examinations using alternative optimization methodologies within the domain of EMS integrated with MG’s. In addition, prolonging the data collecting period outside the current scope would strengthen the study’s conclusions, allowing for a more comprehensive comprehension of the PSO’s performance over a longer length. The suggested PSO optimization in real-world MG scenarios would be greatly enhanced by doing a long-term investigation, which will greatly contribute to its universality and applicability.

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Chapter 6 - Appendice

6.1 Appendix A.

6.1.1 MATLAB Code

```
% Read CSV file
data = readtable('dataset.csv');
for t=1:24
% Extract input and output labels from the first row
input_labels = data.Properties.VariableNames(1:7);
output_labels = data.Properties.VariableNames(8:end);

% Extract data into separate arrays
time = data.Time;
PV = data.PV;
Wind = data.Wind;
EV = data.EV;
Household = data.Household;
% Define system parameters
SOC_BESS_min = 20;  % Replace with actual value
SOC_BESS_max = 80;  % Replace with actual value
BESS_capacity=4.8;
cost_label = 'Cost';  % Replace with the actual label in your CSV file
%selling_cost_label = 'SellingCost';  % Replace with the actual label in your CSV file
cost = data.(cost_label);
%selling_cost = data.(selling_cost_label);
% Objective function
objective_function = @(variables) sum(PV + Wind  + variables(2) + variables(1) - P_from_Grid - EV);
% Constraint function
constraint_function = @(variables) [calculateSOC_BESS(variables) - SOC_min;
                                    SOC_max - calculateSOC_BESS(variables)];
% Particle Swarm Optimization
lb = [0, 0, 0, 0];  % Lower bounds for BESS, Grid, EV, Household
ub = [5, 15, 6, 20];  % Upper bounds for BESS, Grid, EV, Household
initial_BESS_Power= 2;
initial_P_Grid= 5;
initial_P_EV=4;
initial_P_Household=6;
initial_guess = [initial_BESS_Power, initial_P_Grid, initial_P_EV, initial_P_Household];
options = optimoptions(@particleswarm, 'SwarmSize', 100, 'MaxIterations', 100);
optimized_variables = particleswarm(objective_function, 4, lb, ub, options);
% Display optimized variables
disp('Optimized Variables:');
disp(optimized_variables);
% Calculate power values using optimized variables
optimized_P_BESS = optimized_variables(1);
optimized_P_Grid = optimized_variables(2);
optimized_P_EV = optimized_variables(3);
optimized_P_Household = optimized_variables(4);
optimized_P_Total = PV + Wind + optimized_P_Grid + optimized_P_BESS - Household - EV;
renewable_energy(t) = PV(t)+ Wind(t);
Load(t)=Household(t)+EV(t);
if renewable_energy(t)<Load(t) % case 1
  import_to_grid(t)= Load(t)-renewable_energy(t);
```

```
disp('import_to_grid(t):');
disp(import_to_grid(t));
else
Return_to_Grid(t)=Load(t)-renewable_energy(t);
disp('Return_to_G(t):');
disp(Return_to_Grid(t));
end
end
for t=1:24 % case 2
Load(t)=Household(t)+EV(t);
    renewable_energy_BESS(t) = PV(t)+ Wind(t) + BESS_Power(t);
  if renewable_energy_BESS(t)<Load(t)
  import_to_grid_BESS(t)= Load(t)-renewable_energy_BESS(t);
disp('import_to_grid_BESS(t):');
disp(import_to_grid_BESS(t));
else
Return_to_G_BESS(t)=-renewable_energy_BESS(t)+Load(t);
disp('Return_to_G_BESS(t):');
disp(Return_to_G_BESS(t));
end
end
for t=1:24 % Case 3
Load(t)=Household(t);
renewable_energy(t) = PV(t)+ Wind(t);
if renewable_energy(t)>Household(t)
if SOC_BESS(t)<SOC_BESS_max
char1_BESS_Power(t)=4.3-(renewable_energy(t)-Household(t));
disp('char1_BESS_Power(t):');
disp(char1_BESS_Power(t));
else
Return_to_Grid(t)=-(BESS_Power(t)+(renewable_energy(t)-Household(t)));
disp('Return_to_Grid(t):');
disp(Return_to_Grid(t));
end
elseif buying_cost(t+1)>buying_cost(t)
char2_BESS_Power(t)=BESS_Power(t);
disp('char2_BESS_Power(time):');
disp(char2_BESS_Power(t));
else
if SOC_BESS(t)>50
dischar_BESS(t)=BESS_Power(t);
disp('dischar_BESS(t):');
disp(dischar_BESS(t));
else
Import_P_Grid(t)=Household(t)- renewable_energy(t);
disp('Import_P_Grid(t):');
disp( Import_P_Grid(t));
end
end
end
lb = zeros(2 * num_time_steps, 1);
```

```
ub = repmat([BESS_capacity; BESS_capacity], num_time_steps, 1);
objectiveFcn = @(decisions) objectiveFunction(decisions, data, SOC_BESS_min, SOC_BESS_max,
BESS_capacity, num_time_steps);
options = optimoptions(@particleswarm, 'SwarmSize', 50, 'MaxIterations', 200, 'Display', 'iter');
[optimized_decisions, objective_val] = particleswarm(objectiveFcn, 2 * num_time_steps, lb, ub, options);
[SOC_BESS, grid_interaction, renewable_usage] = applyDecisions(optimized_decisions, data,
SOC_BESS_min, SOC_BESS_max, BESS_capacity, num_time_steps);
Charge_Decisions = optimized_decisions(1:24);
Discharge_Decisions = optimized_decisions(25:end);
% Calculate Net BESS Power (Charging - Discharging)
BESS_Power = Charge_Decisions - Discharge_Decisions;
% Plot BESS Power
figure;
plot(1:24, BESS_Power, 'LineWidth', 2);
title('BESS Power Over Time (Charging/Discharging)');
xlabel('Time (minutes)');
ylabel('Power (kW)');
grid on;
function cost = objectiveFunction(decisions, data, SOC_BESS_min, SOC_BESS_max, ~,
num_time_steps)
PV = data.PV;
Wind = data.Wind;
Household = data.Household;
    SOC_BESS = zeros(num_time_steps, 1);
    SOC_BESS(1) = data.SOC_BESS(1); % Initial SOC of BESS
    cost = 0;
 for t = 1:num_time_steps
 Charge_Decision = decisions(t);
 Discharge_Decision = decisions(num_time_steps + t);
 SOC_BESS(t) = SOC_BESS(t) + Charge_Decision - Discharge_Decision;
 if SOC_BESS(t) > SOC_BESS_max || SOC_BESS(t) < SOC_BESS_min
 cost = cost + 1000; % Penalty for SOC outside limits
 end
 remaining_energy = PV(t) + Wind(t) - Load(t) + Charge_Decision - Discharge_Decision;
 if remaining_energy < 0
 cost = cost - remaining_energy;
 end
 if t < num_time_steps
 SOC_BESS(t+1) = SOC_BESS(t); % Update SOC for next time step
 end
 end
 end
```

```
function [SOC_BESS, grid_Ret_Rece, renewable_usage] = applyDecisions(optimized_decisions, data,
SOC_BESS_min, SOC_BESS_max, BESS_capacity, num_time_steps)
 PV = data.PV;
 Wind = data.Wind;
 Household = data.Household;
 SOC_BESS = zeros(num_time_steps, 1);
 SOC_BESS(1) = data.SOC_BESS(1);
 grid_Ret_Rece = zeros(num_time_steps, 1);
 renewable_usage = zeros(num_time_steps, 1);
 for t = 1:num_time_steps
 Charge_Decision = optimized_decisions(t);
 Discharge_Decision = optimized_decisions(num_time_steps + t);
 renewable_energy = PV(t) + Wind(t);
 renewable_usage(t) = min(renewable_energy, Load(t));
 SOC_BESS(t) = SOC_BESS(t) + Charge_Decision - Discharge_Decision;
 SOC_BESS(t) = max(SOC_BESS_min, min(SOC_BESS(t), SOC_BESS_max));
 net_energy = renewable_energy - Load(t) + Charge_Decision - Discharge_Decision;
 grid_Ret_Rece(t) = -net_energy; % Negative for drawing from grid, positive for supplying to grid
  if t < num_time_steps
  SOC_BESS(t+1) = SOC_BESS(t);
  end
  end
 end
numel_optimized_P_EV = numel(optimized_P_EV);
numel_EV = numel(EV);
 figure;
plot(time, PV, 'LineWidth', 1.5, 'DisplayName', 'PV');
hold on;
plot(time, Wind, 'LineWidth', 1.5, 'DisplayName', 'Wind');
hold on;
plot(time, EV, 'LineWidth', 1.5, 'DisplayName', 'EV Load');
hold on;
plot(time, Household, 'LineWidth', 1.5, 'DisplayName', 'Household Load');
plot(time, import_to_grid, 'LineWidth', 1.5, 'DisplayName', 'import_to_grid');
plot(time, Return_to_Grid, 'LineWidth', 1.5, 'DisplayName', 'Return_to_Grid');
plot(time, optimized_P_Total, 'LineWidth', 1.5, 'DisplayName', 'optimized_P_Total');
xlabel('Time');
ylabel('Power (kW)');
title('Energy Management System Results');
legend('Location', 'northwest');
grid on;
hold off;
```