REPUBLIC OF TÜRKİYE

ALTINBAŞ UNIVERSITY

Institute of Graduate Studies

Electrical and Computer Engineering

RENEWABLE ENERGY UTILIZATION IN DEMAND-SIDE ENERGY MANAGEMENT SYSTEM BASED ON LINEAR PROGRAMMING OPTIMIZATION ALGORITHM

Muna Kamel Harmoosh ALMASHHADANI

Master's Thesis

Supervisor

Asst. Prof. Dr. Mesut ÇEVİK

Istanbul, 2023

RENEWABLE ENERGY UTILIZATION IN DEMAND-SIDE ENERGY MANAGEMENT SYSTEM BASED ON LINEAR PROGRAMMING OPTIMIZATION ALGORITHM

Muna Kamel Harmoosh ALMASHHADANI

Electrical and Computer Engineering Department

Master's Thesis

ALTINBAŞ UNIVERSITY

2023

The thesis titled RENEWABLE ENERGY UTILIZATION IN DEMAND-SIDE ENERGY MANAGEMENT SYSTEM BASED ON LINEAR PROGRAMMING OPTIMIZATION ALGORITHM prepared by MUNA KAMEL HARMOOSH ALMASHHADANI and submitted on 09/08/2023 has been **accepted unanimously** for the degree of Master of Science Electrical and Computer Engineering.

____

Asst. Prof. Dr. Mesut ÇEVİK

Supervisor

Thesis Defense Committee Members:

Asst. Prof. Dr. Mesut ÇEVİK	Department of Electrical and Electronics Engineering, Altınbaş University	________________
Asst. Prof. Dr.Timur İNAN	Department of Software Engineering, Altınbaş University	________________
Assoc. Prof. Dr. Aysel ERSOY	Department of Electrical and Electronics Engineering, Istanbul University-Cerrahpaşa	________________

I hereby declare that this thesis meets all format and submission requirements of a Master's Thesis.

Submission date of the thesis to Institute of Graduate Studies: ___/___/___

I hereby declare that all information/data presented in this graduation project has been obtained in full accordance with academic rules and ethical conduct. I also declare all unoriginal materials and conclusions have been cited in the text and all references mentioned in the Reference List have been cited in the text, and vice versa as required by the abovementioned rules and conduct.

Muna Kamel Harmoosh ALMASHHADANI

Signature

DEDICATION

This message is dedicated especially to the spirit of my father who left this world. Special thanks are extended to my mother and all my family for their support and prayers throughout my research project, my classmates and all of my friends have supported and encouraged me throughout my schooling and life, I dedicate my thesis to them, as well as to my advisor, Asst. Prof. Dr. MESUT ÇEVİK.

ABSTRACT

RENEWABLE ENERGY UTILIZATION IN DEMAND-SIDE ENERGY MANAGEMENT SYSTEM BASED ON LINEAR PROGRAMMING OPTIMIZATION ALGORITHM

ALMASHDHADANI, Muna Kamel Harmoosh

M.Sc., Electrical and Computer Engineering, Altınbaş University,

Supervisor: Asst. Prof. Dr. Mesut ÇEVİK

Date: 08/2023

Pages: 61

Demand-side management (DSM) is an effective strategy in smart grid technology to manage energy demand and promoting the efficient use of energy by regulating appliance scheduling and regularly monitoring energy consumption. By integrating DSM into residential energy management, consumers can be empowered to manage their energy consumption and reduce peak demand, which in turn reduces the need for expensive new production and transmission infrastructure. This approach also helps to reduce carbon emissions and enhance grid reliability. To further enhance DSM, optimization techniques can be used to manage large-scale appliances with varying power ratings. By modelling the energy system as a set of linear equations, these algorithms can determine the optimal use of available resources and minimize waste. Linear programming optimization algorithms are a key component of these systems in addition, optimization system based on forecasted cost, power, and energy. By analysing this data, the system can predict when energy prices will be high or low and adjust energy consumption accordingly. This achieved by suggested more than one scenario to test system reliability and used MATLAB/Simulink to simulate the proposed system taking into account various factors such as weather conditions, energy demand, and pricing trends. Compared to other methods using various optimization algorithms, the suggested approach used for lowering electrical energy costs in a microgrid system while maintaining their regular load and operating hours.

By minimizing the energy cost of the community, the algorithm can determine the optimal energy consumption pattern that meets the community's energy needs while minimizing costs. Efficient DSM optimization algorithms can significantly enhance the smart grid's efficiency while reducing electricity costs for consumers. Ultimately, the integration of DSM optimization algorithms can help to achieve a more sustainable and cost-effective energy future.

Keywords: Demand-Side Management, Linear Programming Algorithms, Optimization, Environmental Impact.

TABLE OF CONTENTS

Pages

LIST OF TABLES

Pages

LIST OF FIGURES

Pages

ABBREVIATIONS

IoT	:	Internet Of Things
ARIMA	:	Auto Regressive Integrated Moving Average
ANN	:	Artificial Neural Network
RNNs	:	Recurrent Neural Networks
LSTM	:	Long Short-Term Memory
HEMS	:	Home Energy Management Systems
ICT	:	Information & Communications Technology
SSM	:	Supply Side Management
DSM	:	Demand Side Management
FRTU	:	Feeder Remote Terminal Unit
MAS	:	Multi-Agent System
SHMS	:	Self-Learning House Management System
SCADA	:	Supervisory Control And Data Acquisition
PCA	:	Principal Component Analysis
SVM	:	Support Vector Machines
BI	:	Business Intelligence
POMDP	:	Partially Observable Markov-Decision Process
AMI	:	Advanced Metering Infrastructure Electric Vehicles

EV	:	Electric Vehicles
NILM	:	Non-Intrusive Load Monitoring
NSGA-II	:	Non-Dominated Sorting Genetic Algorithm-Ii
DAQ	:	Data Acquisition
CR	:	Continuous Relaxation
FLC	:	Fuzzy Logic Controller
MILP	:	Mixed Integer Linear Programming
UC	:	Unit Commitment
RES	:	Renewable Energy System
PV	:	Photovoltaics
ED	:	Economic Dispatch
WTGs	:	Wind Turbine Generators
QoE	:	Quality Of Experience
SOC	:	State Of Charge
EI	:	Energy Internet

1. INTRODUCTION

Electricity is an essential resource in modern society, and it powers almost every aspect of our daily lives. However, the production and consumption of electricity can have negative environmental impacts, such as the release of greenhouse gases, which contribute to climate change and global warming. Improving the efficiency of electricity distribution and consumption can help reduce these negative impacts on the environment. For example, upgrading power plants to use cleaner energy sources like renewable energy, such as solar or wind power, can help reduce greenhouse gas emissions. Moreover, improving the efficiency of electricity use can also help reduce energy waste and lower energy bills. For instance, using energy-efficient appliances, such as LED light bulbs and energy-efficient refrigerators, can significantly reduce electricity consumption while providing the same or better functionality. In addition, implementing smart grids that use digital technologies to manage and distribute electricity more efficiently can help reduce energy waste and improve the overall reliability and resilience of the electrical grid. Therefore, by improving the efficiency of electricity distribution and consumption, we can help mitigate the negative environmental impacts associated with electricity production while providing a reliable and affordable source of power to meet the growing energy demands of modern society [1].The three basic operations that make up the power sector are the generating, the transmission, and the distribution of electric power. Power plants are the usual locations where electricity for the electrical grid is generated. The act of bringing high voltage electricity via a substation and lowering it to a lower level is referred to as "transmission," and it is a necessary step in the process. In the end, the electricity is provided to consumers who are located in a variety of locations, including their homes and places of business. The electric power grid is the end result of putting all of these components together[2]. The nation's electrical power infrastructure is currently undergoing the installation of a cutting-edge upgrade referred to as "Smart Infrastructure."

The smart grid plays an essential part in the process of guaranteeing the safe, efficient, and dependable distribution of electricity from generators to consumers in the industrial, commercial, and residential sectors[3]. Using the already established infrastructure of the energy grid, this ingenious method provides essential supplies to individuals who are in need of them. Two of the benefits that result from its two-way communication, which is one of its major assets, are increased reliability and increased efficiency in resource utilization[4]. Additional capabilities include sensing the current status of the power grid, keeping an eye on the power output, and regulating and managing the production, transmission, and distribution of energy [5].

Integration of renewable energy sources such as solar, wind, tidal, and wave power is also made possible by smart grid technologies [6]. Such energy integrations are now essential in order to produce a "greener" environment through the implementation of actions such as the avoidance of pollution, the conservation of energy, and the reduction of emissions [7]. An operation in the grid that is stable, secure, and trustworthy is needed for the expanding usage of renewable sources, which mandates large redevelopments for electrical systems. This is because renewable sources produce less pollution than traditional sources of energy. The flexibility of measurements to be used in a variety of contexts is slated to increase as a result of developments in forthcoming technologies such as the Internet of Things (IoT).

1.1 OVERVIEW

Forecasting the amount of energy that can be generated has become a pressing concern in the power industry as a direct result of recent advances in technology. The forecasting of energy generation is beneficial to power suppliers, the electrical market, and the disputable customer since it helps make operations function more smoothly. Forecasting electricity consumption is essential in the power industry since it assists with a variety of economic and operational activities.

In the realm of energy forecasting, there has been a lot of focus placed on statistical analysis and deep learning algorithms as two forms of prediction technologies. These methods base their forecasts regarding future electricity costs and demand on certain data features in order to produce short-term projections[8]. The major focus of the present trend is on forecasting the price of electricity in the future. The primary allure for corporations is the possibility of monetary gains. In order for utilities to function properly capable meet the desires of consumers, it is essential required make projections about the amount of power that will be generated. Businesses who are in the business of providing power would profit tremendously from having the ability to estimate how much electricity will be generated. It is possible for businesses to enhance their planning without having to reduce their productivity or lose time [9].

The industry has been reorganized, which has resulted in a significant improvement in the accuracy of projections on electricity generation. In the field of electricity forecasting, backpropagation neural networks are utilized rather frequently [10]. Other approaches to forecasting include the Auto Regressive Integrated Moving Average (ARIMA), regression analysis, fuzzy logic, genetic algorithm, and Artificial Neural Network (ANN), which is probably the used choice. Recurrent neural networks, often known as RNNs, have been increasingly popular as a forecasting tool in the power market in recent years. Long Short-Term Memory (LSTM) is a kind of RNN that has demonstrated potential, despite the fact that it has not been utilized to a significant degree for the purpose of energy generation forecasting [11].

The context of lately, the idea for intelligent homes has become more dependent on the Internet of Things (IoT). [12]. It makes it possible for the homeowner to monitor, regulate, and otherwise manage the atmosphere of the house in line with their own preferences. The key areas of focus for research in the field of smart homes are the substructure for connections, the speed and reliability of exchange of information and data security, moreover, the advancement of hardware creation. In addition to this, it has stimulated research into Internet of Things (IoT) technologies for developing the most advanced generation of intelligent dwellings [12][13].

Home Energy Management Systems (HEMS) in intelligent households have been rapidly becoming a topic of considerable attention in academic circles all over the world [14]. We are able to increase the efficacy of the distribution of renewable energy by adding Home Energy Management Systems (HEMS) into smart dwellings. Smart homes are an essential component of the smart grid idea, whereby forms the basis of the relevant electrical power infrastructure that makes it possible to operate in a manner that is more trustworthy, effective, and decentralized. The end result will be a more effective utilization of the available electricity [15]. Supply and demand management mechanism are tended to be built into HEMS in order guarantee more efficient power distribution.

In this work, a novel strategy for estimating the amount of power that will be generated in the future is provided. Our way of predicting has been shown to be more reliable in comparison to those utilized by previous computerized methods.

1.2 BACKGROUND

The Supply Side Management (SSM) system of an energy management system that coordinate power distribution from the many different sources. The source materials feature and the fundamental layout of the distribution framework inform the modifications that may be made to this technique. Using yet another form of intelligent management to govern the amount of energy that is ingested in the electrical grid is called Demand Side Management, or DSM for short. Examples of Demand Side Management (DSM) approaches include Demand timetables, demand management, and load shedding [16]. Because of the introduction of "Peak" and "Off-Peak" hours in the market for electrical services, strategic planning and operations have assumed an increasingly important role for companies [17].

By moving their activities to "Off-Peak" periods, when rates are generally cheaper, many firms may save money and increase their profitability. However, there is still the possibility of malicious behaviour, such as the theft of energy.

In many countries, the problem of theft involving important energy resources is getting worse. However, to this day, there have only been a relatively limited number of preventative measures created for energy theft [18]. A dynamic programming strategy was proposed by Zhou, Y. et al. as a method for using Stochastic energy theft identification in intelligent houses. Customers would incur additional expenses if the proposed solution is put into action since it requires the installation of a Feeder Remote Terminal Unit (FRTU) on top of a smart meter. Smart meters already come at a premium price[18].

In addition to that, it is necessary for there to be a smart meter currently in operation. Because of this, the installation of a new system to detect and prevent energy theft will result in an increase in the reliability of energy transmission. Nevertheless, in order for these systems to work, there must first exist an efficient communication infrastructure.

According to the findings of a number of studies , some of the many areas of interest for agents working in the industrial sector include timetables, facilities allocation, Management, instantaneously planning, and a strategy process [19]. These are only some of the numerous areas of interest. S. D. J. McArthur and colleagues [20]came up with the idea of a Multi-Agent System (MAS) [21] as a probable approach. When MAS is implemented into the smart home system, the agent's behaviour may be simply altered in result of alterations affecting the environment. It is widely recognized for quite some time that the heterogeneous network environment that is present in a smart home plays to the strengths of MAS network management, control, parallel program generation, and computer communication [22].

It has been shown that the MAS is capable of functioning as an intelligent agent-based communication system that can be utilized in a smart grid. This system is comprised of a number of agents or intelligent agents that are able to communicate with one another in any given environment. An item of hardware or software that modifies its behaviour in response to stimuli from the outside world is referred to as an agent.

Computing can be done more quickly when using MAS in HEMS for smart homes since it streamlines the flow of data between the various agents. Homeowners are able to monitor their own energy use and make adjustments to their systems according to their preferences thanks to smart meters. "Advanced applications," such as Supervisory Control and Data Acquisition (SCADA), which contains optimization features, perform the responsibilities of monitoring and controlling. These functions are supplied by "advanced applications." However, previous research on the idea of smart dwellings did not take into account the prospect of self-learning algorithms for the application of collected data.

It is general known that machine learning is an intriguing technology that may be used in smart homes. Because it is capable of making choices on its own, it may be included into systems that provide intelligent control of the home's energy use. In order to deliver the most effective solutions, machine learning conducts research on previously collected data to identify patterns in user activity [23]. Because it is able to adjust to various environments and circumstances, HEMS has the potential to effectively teach itself.

This study suggests a breakthrough method for developing a demand-side energy management system that makes use of linear programming optimization algorithms so that such systems could enhance the usage of renewable energy sources while lowering tariffs for energy. t might result in reduced peak energy demand by resulting in significant cost savings for energy providers and consumers alike.

1.3 OBJECTIVE

A primary objective of this project is to optimized energy management systems in energy cost minimization. Energy cost minimization without load shifting or load shading is the main principle of working in the proposed system. In addition, an electrical generation forecasting system was developed, and its accuracy was validated by contrasting it with methods that are considered to be more conventional.

The findings of this study lay the groundwork for smart homes to become more self-sufficient, cost-effective, and energy-efficient in the future. People will have a better understanding of how much electricity they actually consume once they are capable of tracking and gauging their own usage energy consumption. As a result, this avoids the use of excessive amounts of electricity, which in turn keeps circuits from being overloaded.

1.4 OUTLINE

The remainder of this dissertation will be organized according to this framework.

To get started, Chapter 2 provides an overview of the research's literature, which includes not only the proposed systems but also the background of those systems. Second, Chapter 3 provides an overview of the techniques and processes utilized by the prediction system. Thirdly, both the outcomes of the simulations and the predictions made by the systems are provided in Chapter 4. In the last chapter of this dissertation, I will review the findings I've gathered and talk about the goals I have for the future.

2. LITERATURE REVIEW

This area provides you with the materials you need to learn more about the electrical market, smart homes, HEMS, machine learning, and MAS. This section also offers information regarding IoT. The data obtained from a smart home, in general, indicates the hardware, software, and algorithm that may be utilized to develop a setup that is more efficient with its use of resources. In following sections of the thesis, the significance of these resources and the manner in which they operate on their own will be further upon.

Throughout this literature review, we will examine past research and the manner in which we used the findings from other studies to influence our own investigation or experiment. The literature's assessment of knowledge gaps might provide insight into the research motivations behind previously published publications.

2.1 SMART HOME

The "smart house" actually an essential element related to "smart grid". In a body of research that was carried out by Autonomous Electricity Framework Administrator [23], the term "Smart Grid" was defined as a modern electricity system that makes use of users' sensors, communications, automation, monitors, and computers to enhance the system's security, reliability, scalability, Effectiveness as well as security. This was done in order to make the system more modern and efficient. The smart grid is made possible by computing power and technologies that allow for two-way communication. Because of its time-tested dependability and low overall power requirements, this two-way communication technology has found widespread use across a variety of industries in recent decades. It is able to sense conditions on the grid, measure power, and regulate appliances because to its capabilities of communicating in both directions with the various stages of energy generation, transmission, and distribution. An intelligent power grid is one in which each component has the potential to make modifications all by itself in order to attain the highest possible level of energy utilization effectiveness

The expression "smart home" is commonly used to describe a dwelling that is outfitted with a system that can interact with other systems in the home via a network connection and is therefore regarded to be a feature of the smart grid. The aforementioned type of dwelling has become known as a "connected home." The linked home is seen here from a more generalized point of view in Figure 2.1.

In a smart home, the power supply and the gadget that allows for interaction are both handled by the smart meter. Traditional electromechanical meters will soon be phased out in favour of their digital counterparts, the "smart meters," which operate in a digital manner and allow for complex information to be shared between residences and energy companies [24]. The smart meter is able to receive signals from the utility provider, which assists in keeping the home's overall level of energy use consistent. The monthly payment for energy is reduced, and more accurate information on energy consumption is compiled.

On the other hand, a smart appliance is one that can be accessed and managed through the use of an electronic network. These kinds of home appliances are able to react to signals that are transmitted by the smart meter and turn off anytime there is a low demand for power. According to Ramchurn et al. [25] the smart grid introduces substantial additional issue to the field of agent intelligence. This is because the smart grid necessitates the development of algorithms and methodologies that are able to solve problems that include a large number of extremely different participants. When it comes to smart houses, according to the same article, there are a number of different strategic aspects that need to be researched. Electric vehicles, self-healing networks, energy prosumers, and virtual power plants are a few examples of these technologies.

The early adoption of standardization has resulted in the current market for smart appliances with a large variety of brands, each of which employs a technique of communication that is only slightly different from the others. In this world of different devices and protocols, adopting a standards-based approach on the growing smart home is very necessary. Because of this, in the long term, system administration will become significantly less difficult as a result of a reduction in the requirement for recurring maintenance operations [26]. Sensors to detect their environs, device controllers, programming units, an interface network for communication, and smart meters to measure energy usage and user conduct are common components found in smart houses [27].

Integration with the vast majority of already existing networking protocols and technologies, entity interfaces, as well as home-based software and services is a big obstacle for the smart home idea. Installing an array of solar panels as a source of clean energy is one of the options available.

Corno and Razzak [28] suggested an intelligent energy optimization with the purpose of achieving user-comprehensible goals in the context of smart homes. In an effort to establish efficient local energy management systems and cut overall power consumption, it takes into consideration the utility business as well as individual users. The Demotic Effects modelling framework, which is described in Boolean form, is a strategy for addressing the demands of users and generating satisfactory power outputs within the constraints of time. This experiment concentrates primarily on components of the house; hence, a great deal of household appliances was not taken into consideration. There are many other things happening in the world outside only the enhancement of a smart house. The customer's way of living can have an impact on the amount of money spent on electricity. For instance, if the consumer is able to use his appliances during off-peak hours, this can help him save money.

An electricity market, machine learning, a multi-agent system, the Internet of Things, and a Home Energy Management System are examples of the kinds of software and hardware components that may be found in a smart house (HEMS).

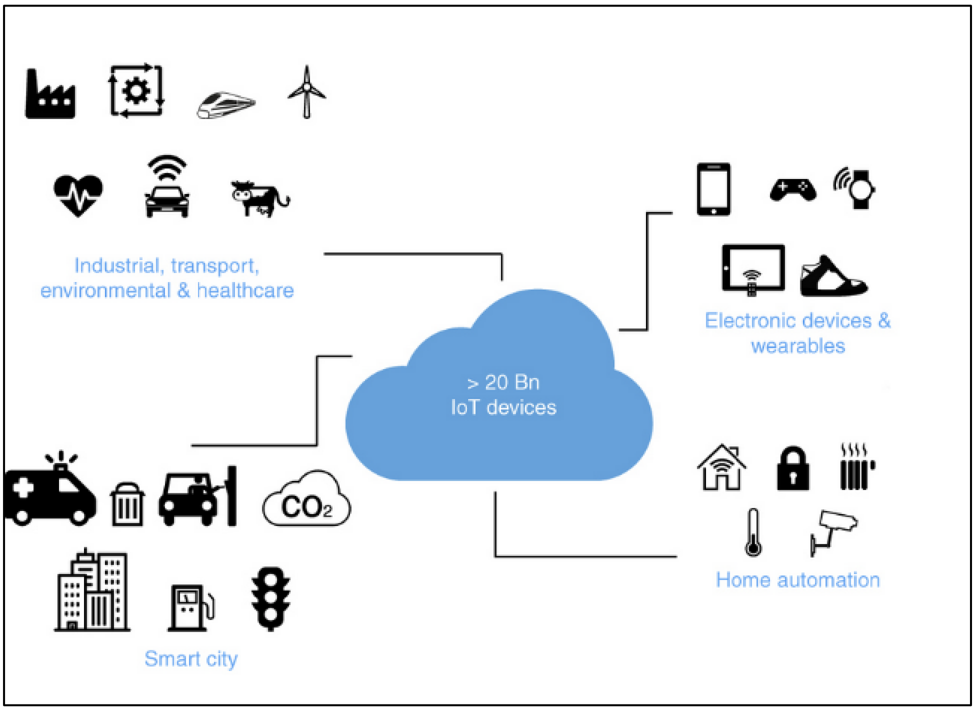

Figure 2.1: Relationships Among Internet-Of-Things Gadgets.

2.2 MACHINE LEARNING

Machine learning is a branch of artificial intelligence that examines databases in order to "teach" computers new skills [19] This allows computers to "learn" new skills on their own. It is possible for the computer to learn using this strategy even without input from a person. Its principal purpose is to educate itself independently using the information that you supply it. The initial phase in the learning process is to conduct an analysis of the database to look for replies that are compatible with the instructions that have been given. After gaining an understanding of the patterns exhibited by the data, it is able to make decisions that are more well-informed. Figure 2.2 illustrates the differences between supervised and unsupervised learning processes.

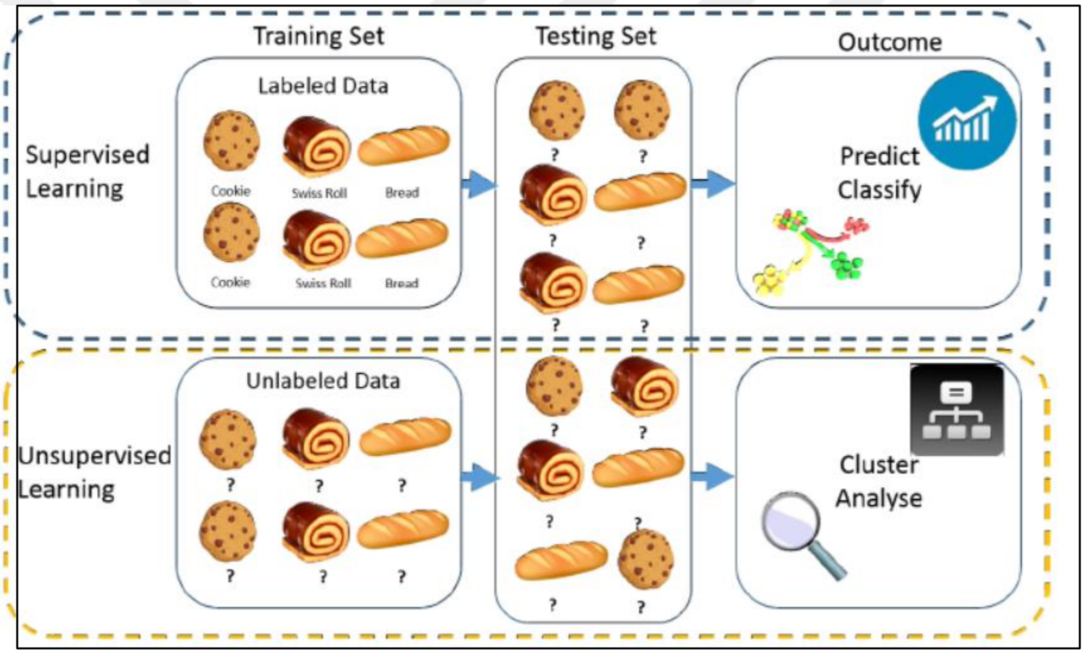

Figure 2.2: The Agent Interaction Diagram.

2.2.1 Supervised Machine Learning Algorithms

It applies the learnt algorithm by evaluating and classifying previously collected data in order to create predictions about newly acquired data [29]. The learning algorithm is generated with the help of the training dataset, while the testing dataset is used to check that the algorithm is working correctly with the data that was intended for it to work with. If the results are not satisfactory, the method can be used to make adjustments to the model in order to get a better result.

2.2.2 Semi-Supervised Machine Learning Algorithms

An innovative way to learn that blending supervised and unsupervised approaches to the subject matter. mainly due to the fact that it can be trained and tested on both labelled and unlabeled data [30]. Data that has been tagged will frequently be of a lower quantity than its equivalent that has not been labeled. As a consequence of this, there will be a reduction in the costs associated with data labeling.

2.2.3 Unsupervised Machine Learning Algorithms

as opposed to other machine learning approaches, such as supervised machine learning, it applies the recently acquired algorithm to unidentified or uncategorized data. [31]. There is no way to check whether or not the system is accurate, but it may detect patterns in the data and form judgments about how to move forward.

2.2.4 Reinforcement Machine Learning Algorithms

It's an instructional approach that, as it progresses, works out how to better itself [32]. Robots and software agents can utilize reinforcement learning to figure out what actions to take so that they can achieve the highest possible level of their own performance. Without this fundamental incentive feedback, agents are unable to learn the best way to respond to a situation.

2.3 RENEWABLE ENERGY

Renewable energy nowadays is one of the more significant energy sources so many researchers studied its behaviour, control, losses, and other related things. In 2016 Akel Fethi [33] and others studied power flow controlling of grid-connected single-stage PV system. The study showed that the injected current by the PV system into the grid obeyed grid standards. And the system performed other tasks like reactive power composition and harmonics elimination. They also suggested more than one scenario to test system reliability and used MATLAB/Simulink to simulate the proposed system. That system as they concluded controlled by the space vector modulation technique SVM and tracked all possible real power created by the PV array while voltage at the shared linkages region PCC was motioned to be stable and the real and reactive power components were isolated in controlling i.e., reactive power compensation independent on real power generated by PV array.[34] Wei Yi and others in 2017 proposed a modelling simulation of a DC microgrid. In that presentation, they studied renewable energy sources connected to DC microgrid which is called a virtual DC generator VDG that is controlled by a virtual synchronous generator also called VSG. They had given completed circuit topology and the strategy of control. The proposed grid-connected generator has transcended the drawbacks of imitative grid-connected inverters; therefore, it is easier to consent to grid-based renewable energy. Finally, they detected that the recommended technique likely embedded in hybrid distribution networks. And the control strategy of virtual generators VG enhanced the overall system control.[35] In 2018 Mahmoud Nour Ali proposed an artificial intelligent-based maximum power point tracking MPPT system. Artificial neural networks ANN are used to perform the MPPT controller but he also suggested the use of the genetic algorithm to design ANN. The proposed ANN MPPT system depends on PV array voltage and power as additional inputs for the control system. simulation results list the proposed system had higher performances than traditional MPPT systems like perturb and observe P&O and incremental conductance.[36] In 2018 Prashant Kumar Singh and Dr. Anil Kumar Dahiya introduced modelling analysis and simulation for grid-connected PV systems and D-STATCOM. Two control loops were proposed, a voltage or outer control loop and an inner or current control loop for real and reactive power composition. MPPT system implemented using perturb and observe P&O algorithm owing its simplicity and minimum input parameters requirement.[36]

This underlines the lack of effective forecasting tools for estimating future energy generation. The use of artificial intelligence will be extremely beneficial to the development of home automation technologies, such as those that help homeowners save money on their utility bills or make their lives simpler overall. Because of this, HEMS is one step closer to being an intelligent and energy-efficient house thanks to the incorporation of AI into its energy management system.

2.4 ELECTRICITY MARKET AND OPTIMIZATION ALGORITMS

The market for the commodity determines the price of the electricity needed to run a smart home. Auctions are performed often so that electricity suppliers can buy, sell, and trade their wares [37]. The stock market is one example of a market that is driven by supply and demand, and the bid and offer prices reflect this dynamic. Power is frequently transacted via long-term contracts due to the complexity involved in establishing new connections to the grid. The cost of electric power would play a vital aspect in this notion given that customers are the ones who are ultimately responsible for footing the bill for these services through their usage of electricity via the power grid.

Chen, X. et al. [38] presented an idea for scheduling household appliances in an approach that looks into the electricity cost fluctuating while also accounting for uncertainty. A recommended algorithm has been devised to set up policy for operation of domestic apparatus in a manner how to decreases customer's financial outlay. This algorithm is built using the basis of the time-dependent price model that energy market uses. By parallelizing the computational procedure, the recommended equipment function arranging algorithm also speed up the creation of timeline for intended operations. However, because it emphasizes on financial costs, it is missing studies on energy usage and how it will alter consumer habits.

Several effective algorithms, including the sparrow search algorithm (SSA), cockroach swarm optimization (CSO), and binary orientation search algorithm (BOSA), were used to DSM approach for a housing area with base target of minimizing maximal energy consumption. The smart grid may ultimately become ever more effective while also being more affordable to use due to algorithm-based optimal DSM. In this regard, the suggested DSM technique takes a load-shifting utilization mechanism [39] . whereas [40] stated that in order to constrict overall costs and the peak-to-average ratio (PAR), a linear programming (LP)-based mechanism to manage the consumption of energy in households. An integer linear programming (ILP) strategy is used to control scheduled power and time-shiftable equipment was suggested in [41].

In accordance with a theory advanced by M. A. A. Pedrasa et al. [42], as a way to improve functionality of smart home energy use, a synchronous arrangement to propagate of power resources was necessary. Particle swarm optimization is applied to enhance decision-making aids by coordinating the use of decentralized power generation and enhancing the efficiency with which families may purchase electrical power. Particle swarm optimization is used to improve decision-making aids.

Hansen et al.[43] Suggested a Partially Observable Markov-Decision Process POMDP strategy for the regulation of domestic energy use. The technique uses a myopic POMDP strategy in addition to two non-myopic POMDP strategies to lower the costs of household power usage in an environment with dynamic pricing. One of the non-myopic POMDPs, which offers a cost advantage spread out over a period of months, might be of use in the management of energy usage at home.

A representation of a possible structure for the electricity market is shown in Figure 2.3.When it comes to the electrical market, precise foresight is absolutely necessary for the intention of utility company strategy and execution [44]. An exaggeration of electrical production leads to provide an excessive amount of energy, which in turn drives up operational expenses for no discernible reason. If the forecasts turn out to be too low, businesses will be obliged to build expensive emergency peak capacity and make expensive, inevitable purchases for the generations who will come after them [45]. Due to the adversarial nature of this trade-off, expenditures for implementation of a UK power supplier increased by £10 million in 1985 as a result of an estimated 1% forecast inaccuracy. If this problem is resolved in a way that leads to the creation of greater precision forecasting system, it will be possible for notable improvement of energy supply and routing system's dependability while simultaneously reducing the costs of maintenance and repair [46]. As a result, it is essential for the smooth operation of future smart home power grids, which must prioritize safety, efficiency, and cost-effectiveness.

There are a few advantages that come along with accurately predicting the amount of electricity that will be generated [47].

view of the long-term forecast for energy generation in order to be able to make decisions that are financially sustainable about future investments in electricity generation and transmission. This makes it possible to arrive at a more precise estimate of the amount of fuel and other supplies that will be required to keep the power plants operating and the supply of energy to consumers uninterrupted and at a cost that is affordable. This knowledge is helpful for developing plans for the near future, as well as plans for the intermediate and long-term future. It is helpful to forecast future energy generation in order to decide where and what sort of power plant should be built in the future, as well as how large it should be. It is expected that utilities will site power plants near the load by identifying locations or regions with strong or growing demand for electricity and then moving power plants there. Because of this, there is a decreased requirement for transmission and distribution systems, as well as the losses that are associated with such facilities. Helps in making decisions and formulating strategies for the upkeep of the power system. If utility providers are aware of their generation, they may arrange maintenance work to take place at times of the day when it will have the least amount of impact on their consumers. For example, they may plan maintenance for residential areas to take place in the middle of the day, when the majority of residents are at work and demand is at its lowest point. Maximum use of power plants to the extent that they are capable. The process of forecasting helps to prevent either an inadequate or an excessive amount of generation.

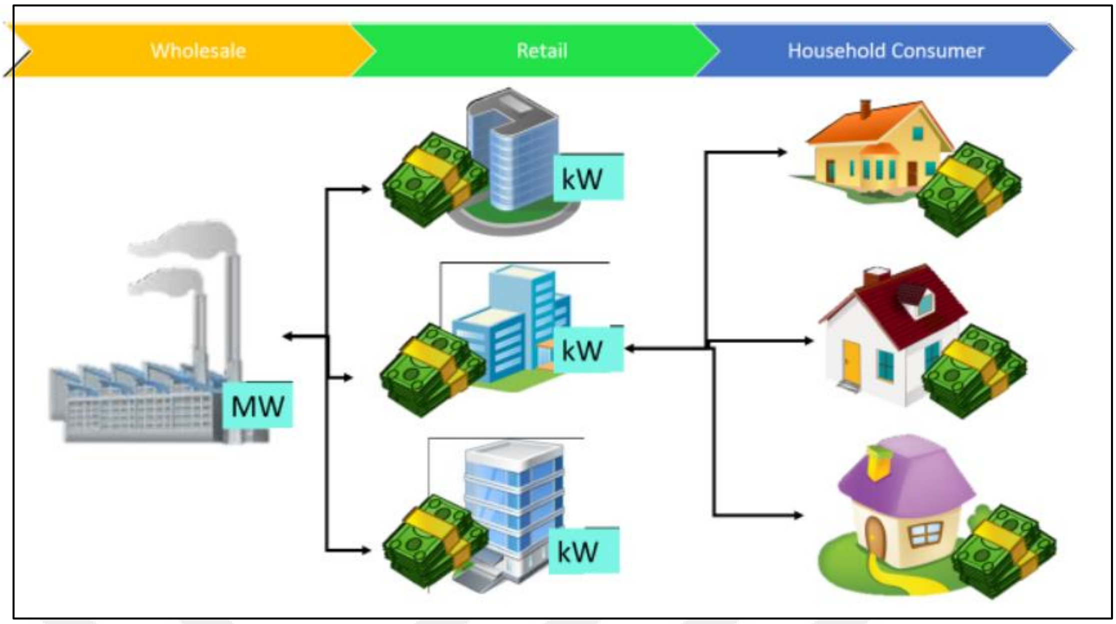

Figure 2.3: Structure Of Electricity Market.

2.5 HOME ENERGY MANAGEMENT SYSTEM (HEMS)

Thru the execution of the Internet of Things (IoT) and smart meters, smart homes can be created. Home Energy Management System (HEMS) is an integral component for monitoring and controlling the Advanced Metering Infrastructure (AMI). infrastructure of the system [48]. HEMS is a smart home software system that monitors, controls, it enhances the production, distribution, and use of electricity in smart grids. A smart meter, which performs tracking and regulating operations, is a crucial part of HEMS. The "advanced applications" section of HEMS is responsible for optimizing. Utilizing mobile devices, HEMS, for instance, enables customers to easily manage smart home appliances. One of the forthcoming patterns is the incorporation of Smart houses can use electric vehicles (EV) as a movable, renewable battery. The use of smart houses will result in the widely utilized of electric vehicles in the next years, which will alter the energy requirements of transportation from conventional fossil fuels to electricity. Due to the limited capacity of EV batteries, HEMS in smart homes will require faster charging rates for EV batteries [49] shown in Figure 2.4 Overall architecture of a HEMS. Lin, Y. H., and Tsai, M. S. [50] suggested a novel HEMS supported by a non-intrusive load monitoring (NILM) technique with an integrated multiple-target in-home energy scheduling technique based on the Non-Dominated Sorting Genetic Algorithm-II (NSGA-II). In Taiwan, the strategy is employed for data collection and load management in a real-world home setting. However, the study only used specific home appliances, and it necessitates considerable rewiring of the household's electrical system utilizing National Instruments Data Acquisition (DAQ) equipment.

Wu et al. [14] proposed Continuous Relaxation (CR), Mixed Integer Linear Programming (MILP), and Fuzzy Logic Controller (FLC) management for the HEMS rolling optimization. The three methods' objectives are to manage and watch out for heating, task-specific, and battery power using computing resources, cost savings, and applications in the real world. Although they require more computing time, all three approaches can optimize consumption of energy within to the optimal cost. For the purpose of reducing the local cost of controlled devices, the suggested solutions are integrated into HEMS.

Joo, I.Y., and Choi, D.H. [51] Utilizing a algorithm for distributed two-level HEMS optimization , this method minimizes The overall cost for electrical power while preserving temperature control for several houses using distributed energy resources.. The suggested distribution algorithm achieves nearly identical performance to a centralized algorithm based on electricity cost and consumer convenience.

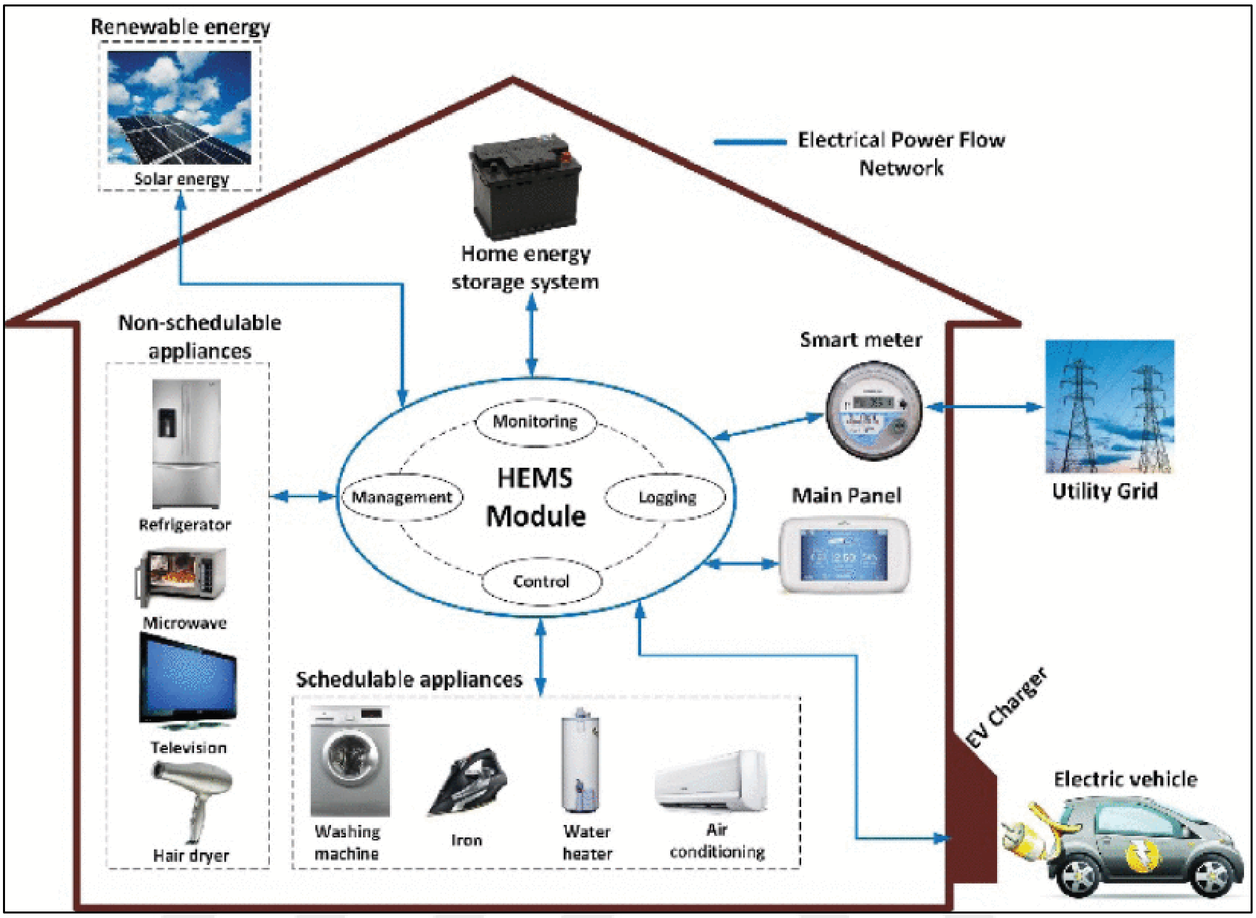

Figure 2.4: Overall Architecture Of A HEMS.

2.5.1 Supply Side Management (SSM)

Supply Side Management (SSM) is a strategy in HEMS [23] for optimizing electrical supply from several power sources. Generation scheduling is the term used for SSM in energy management systems. While taking into account the limitations of the systems, it plans the production of power from various generation units over an interval of time. Objective SSM functions include the costs of integrated energy productions, start-up and shutdown choices, and anticipated profits. This generates large-scale nonlinear optimization issues. Two sub-problems comprise SSM issues: Unit Commitment (UC) and Economic Dispatch (ED). The UC issue determines whether generators are ON or OFF during a predetermined period, whereas ED problem determines the operational Generator efficiencies are dependent on how much it costs to operate. Many power generators comprise the contemporary power system, with the number of generators increasing over time to satisfy rising electrical demand. This issue may necessitate additional restoration period owing to alterations the physical infrastructure. Consequently, the development of SSM capacity to solve issues would have a significant impact on HEMS, leading to a significant system shift [52]. Intelligent energy distribution management would be one of the most important concerns for forthcoming energy supply systems, smart houses and smart appliances. The problem could be addressed by redistributing electricity from its supply sources. constructing a system with an optimal algorithm to maximize the efficiency of HEMS's use of power [53] would contribute to the improvement of electrical efficiency.

According to Schweppe et al., there are a number of reasons why power demand should accommodate supply circumstances [54]. It seemed obvious that a long-term contract for more economical production required a decline in power demand in order to build an efficient system at a lower cost. Hence, an effective electrical system would be one where supply and demand are properly balanced. Kahrobaee, S. et al. [55] It entails the development of an electrical System for management using random variables such as the speed of the winds, power costs, and load. The most optimal system size for wind energy generating and batteries is then determined by a three-stage combination randomized strategy utilizing particle swarm optimization and Monte Carlo simulation. Although this simulation useful for assessing storage capacity concerning smart homes, this experiment did not include adopting apply of alternative renewable energy sources. One essential element of smart house is a Renewable Energy System (RES) for reducing carbonization. Diverse nations encourage the usage of RES to decarbonize conventional power plants. This results in a rapid increase in the usage of renewable energy sources like solar, wind, and tidal when provide electricity for the grid. Photovoltaics (PV) systems convert solar radiation into electricity using solar cells [56]. Considering its depends upon sunshine straight, it is most effectively during early morning and late at noon before sunset. Typically, a solar tracker is installed on rooftops, buildings, or grounds to keep track of the sun. Depending on the situation, a PV system may be wired to the grid or to a battery system. Electrical corporations commonly run wind turbine generators (WTGs), which are powered by windmills. Windmills are typically located near areas with strong winds, whether on land or at sea. As a major drawback, the wind's direction and speed have a substantial impact on how well wind energy may be used. Hence, wind power output is dependent on climatic circumstances; consequently, its production may change as time passes.

Electricity can also be generated by using sort of renewable energy known as tidal energy that make use of waves of the tide. It might be generated on a daily basis, making it an effective resource for the creation of energy. In contrast to solar and wind energy, tidal energy is not impacted by exterior weather conditions, which is an advantage [57].Moreover, tides are easily predictable. Renewable energy supplies 19% of the world's current power consumption, with hydroelectric energy producing 16%; wind and photovoltaic energy productions are very minor[58]. Using RES to power smart homes indicates numerous opportunities for improvement.

Pilloni, V., et al. suggested Quality of Experience (QoE) intelligent home energy managing system with renewable energy sources [59]. When renewable energy sources are deployed, using two systems of algorithms based on time-of-use pricing, and taking notice of user behaviours, this approach intends to decrease the power cost while retaining the QoE perceived by consumers. N. Javaid et al. [60] presented a smart management of loads solution for intelligent homes that utilizes renewable energy. The method employs binary particle swarm optimization, cuckoo search, and genetic algorithm to develop a demand side management model based on evolutionary algorithms for rescheduling the appliances of residential customers. The suggested approach dramatically lowered home electricity bill peaks and costs. Melhem, F. Y. [61], presented optimization and energy management in smart homes with photovoltaic, wind, and battery storage system integration [62]. The approach optimizes energy consumption and production by integrating battery storage systems, renewable energy resources, and electric vehicles using a mixed integer linear programming model. Via a study's experimental design with the Taguchi approaches for three instance studies, the recommended method significantly reduced energy costs and demonstrated the global optimal response. RES cannot replace current electrical grids because they have been constructed and utilized for decades. The unpredictability of renewable energy sources owing to the climate or weather necessitates adaptable operations to support dependable integration and development. For RES to be viable for sophisticated control and monitoring, various criteria must be met, such as dependability, efficiency, and algorithm development. Therefore, to research this technology, it is critical that the necessary equipment and instruments must be accessible. Regardless the fact that RES technology cannot meet the demand for electricity in the present day, it is still a viable option. Yet, integration with the existing electrical grid has demonstrated that it can alter the system to some degree [63]. A battery storage system is vital for storing energy for usage during emergencies or high demand periods. Rechargeable batteries have typically been used in off-grid battery storage devices to store surplus power. A disadvantage of such a system, however, would be the requirement for costly upkeep. Grid-connected systems use the transmission grid as a storage medium and allow surplus electricity to be returned to it.

2.5.2 Demand Side Management (DSM)

Demand-Side Management (DSM) attempts reducing energy consumption while guaranteeing consumers' highly reliable electricity distribution. [64]. If more electricity is utilized during off-peak hours in contrast to peak hours, consumers' electricity bills could be considerably reduced due to lower power tariff pricing. DSM contributes to reducing consumer electricity bills and increasing the effectiveness of electricity use for this reason. Consequently, it performs a crucial function in the HEMS. Chen, X., et al. offered a scheduling approach for home appliances that considers dynamic power cost and is uncertainty aware [65]. The method introduces a new demand side management strategy to organize household equipment for operating to reduce costs in response to the problems of fluctuating renewable generation and unpredictability in household appliance time of use. As compared with standard home operations, the recommended approach can cut costs by as much as 41%. Di Giorgio, A. and Pimpinella, L. put forward a home automation management that works on events that would enable automated demand side management and consumer economic savings.[66]. To enable effective regulation of electrical energy in a home context, the notion advocated building of a smart house controller approach. By means of time-of-use pricing and DSM, the suggested formulation maximizes overload control and financial savings.

Khalid, A. et al. pushed for the application of various energy efficiency goals for demand side management in smart buildings and dynamic coordination of home appliances [67]. The concept involves applying to enhance the energy expenditures in smart homes, use demand side management's load shifting technique. Through regulating residential appliances, it intends to reduction of energy cost and the maximum versus standard amount while preserving convenience of users. Current strategies to reduce consumption of energy have been confined to either directly managing the Electronics for shoppers (i.e., discontinue high-load facilities, like conditioning units, automatically in rush hours) or via offering clients pricing that, as a result of the wholesale power market, restrict usage of electricity at peak hours[68]. Since smart meter readily available, it is feasible to do an instantaneous assessment of how much electricity is used, allowing all residential, trading, and manufacturing customer to respond to grid signals by automatically minimizing load. The primary difficulty in adopting Artificial Intelligence (AI) in DSM is heterogeneous device's decision-making design. Based on forecasts of future supply and demand, AI acquires the ability to react to up to date electricity usage and costs. It was common knowledge that decreased demand leads to cheaper manufacturing and lengthier continuing deals, causing in a less expensive and more effective grid [69]. The figure 2.5 showing both SSM and DSM.

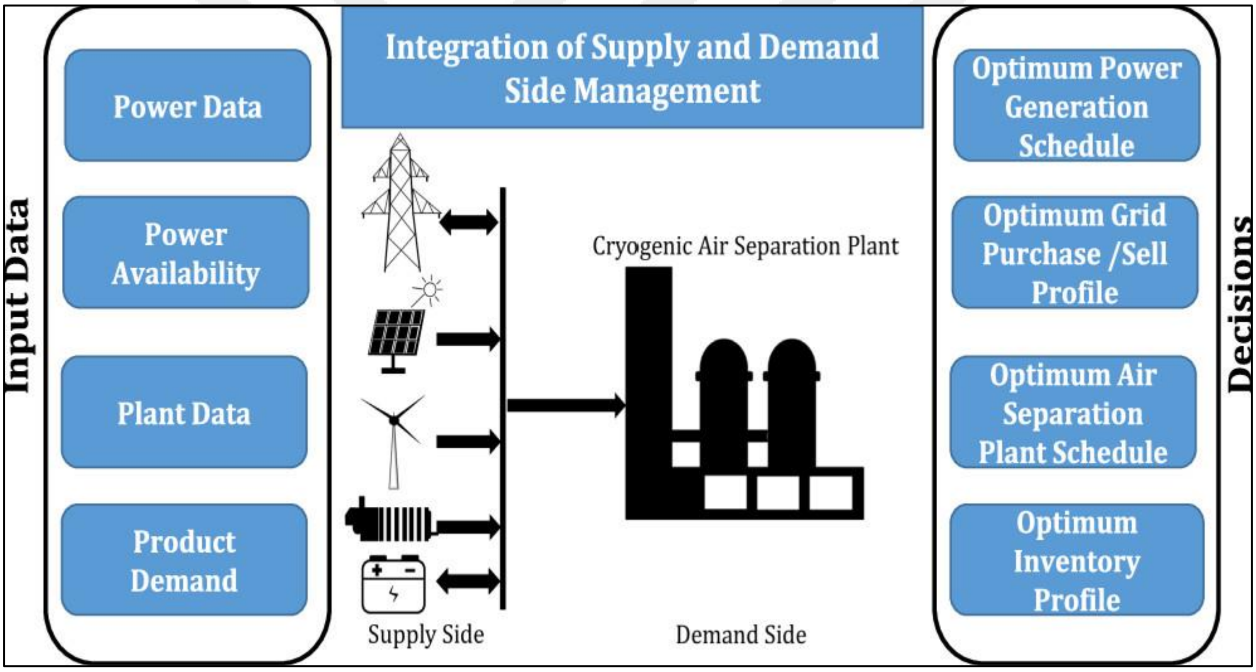

Figure 2.5: SSM and DSM.

2.6 ENERGY INTERNET

The notion of the "Energy Internet" describes how digital technology along energy from renewable sources can be coupled with the electrical infrastructure to produce a more effective energy system, sustainable, and decentralized. It envisions a system in which energy is generated, stored, and distributed in a more flexible and efficient manner, with customers actively monitoring their energy consumption.

The Energy Internet consists of several essential elements:

a. Distributed Energy Resources (DERs): DERs include renewable energy sources like heliacal, wind, and geothermal power, along with energy storage technologies like batteries and flywheels. These resources are typically positioned near the point of use, such as on rooftops or in communities, and can be connected to the grid via microgrids or other distributed energy systems.

b. Smart Grid Technology: The Energy Internet employs cutting-edge digital technology to manage the flow of electricity, monitor energy use, and optimize the distribution of energy resources. This incorporates sensors, communication networks, and automation technology.

c. Energy Marketplaces: Energy marketplaces allow people to buy and sell energy without relying entirely on traditional utility corporations. These markets establish a secure and transparent environment for energy trading using block chain technology.

d. Energy Management Systems that enable consumers to keep track on and manage their energy usage in real-time, as well as provide advice for optimizing energy consumption and decreasing expenses.

The Energy Internet offers various benefits, including:

a. By merging technology for smart grids and green energy sources, Energy Internet is qualified for eliminate power waste as well as optimize the distribution concerning power resources, resulting in increased energy efficiency.

b. Reduced Carbon Emissions: The utilization of renewable energy sources in the Energy Internet can lower pollution and even carbon emissions associated with conventional electricity generation based on fossil fuels.

c. Increased Energy Independence: The Energy Internet can provide consumers more control over their energy consumption and lessen their reliance on conventional utility corporations.

Ultimately, the Energy Internet proposes a new vision for the energy of the upcoming years, where green electricity sources and digital technology are merged to produce a decentralized, greater efficiency, and environmentally friendly power source [70][71].

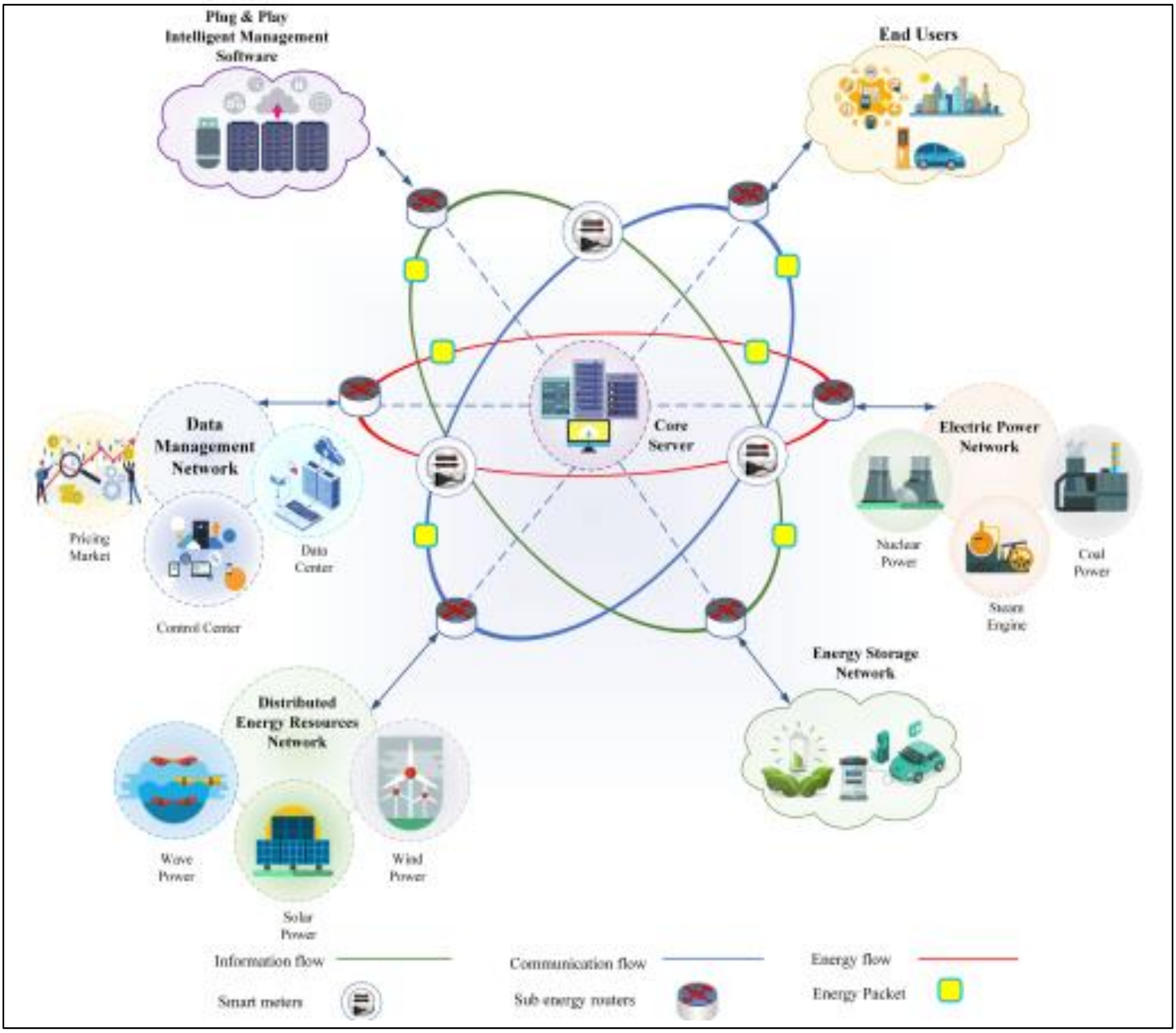

Figure 2.6: Basic Components Of An EI With Various Networks.

Since there are many methods have been used in other research using different types of optimization approaches. Therefore, we summarize these several methods as In table2.1:

Table 2.1 Below Is A Summary Of Previous Studies.

Table 2.1: Summary Of Literature Review.

No	Year	Author	Methodology	Results
1	2012	Corno and Razzak	Intelligent energy optimization with the purpose of achieving user-comprehensible goals in the context of smart homes.	Consumers may save money on their monthly power bills by using their appliances during off-peak hours.
2	2023	Jasim, A.M.; Jasim, B.H	effective algorithms for a housing area with base target of minimizing maximal energy consumption	Minimization of consumption while load-shifting utilization mechanism
3	2013	Chen, X. et al.	Energy efficient scheduling algorithm	Rather than investigating energy use and its impact on customer behaviour, it prioritizes cutting costs.
4	2011	Kantarci, M.; Mouftah	linear programming (LP)-based mechanism to manage the consumption of energy in households.	Consumption is done with scheduled power and time-shiftable equipment
5	2021	Y. Ma, X. Chen	the HEMS design and the best planning technique. The smart home, new energy generation, energy conservation as well as the smart grid and demand response (DR). Additionally, future development directions and the best timing for power-consuming devices and power resources in the HEMS are explained	Power equipment can compute and combine the detected data to arrive at the appropriate conclusion and transmit it to the user via artificial intelligence

Table 2.1: Summary Of Literature Review "Table Continued".

6	2016	Hasan	Partially Observable Markov-Decision Process POMDP strategy for the regulation of domestic energy use	The work's intended outcomes would have far-reaching positive effects on global sustainability, both economically and socially.
7	2017	S.Baker et.al	Intelligent polling and event detection method.	Bandwidth needs and missed power events are both minimized in a real-world Insteon network because to the use of clever polling and event detection techniques.
8	2018	P.-H. Kuo and C.-J. Huang	A system for predicting electricity prices utilizing (LSTM) and (CNN), two deep neural networks. The (MAE) and (RMSE) assessing metrics were used to compare the overall performance of each algorithm	The suggested EPNet has the least average MAE and RMSE scores and excellent estimating accuracy. Also, it proves that the proposed model, which combines CNN and LSTM, could be achieved and useful

3. METHODOLOGY

The proposed system is a smart grid optimization system that uses forecasted cost, power, and energy to minimize energy costs and promote a more sustainable future while keeping the demand within normal levels. The system likely uses optimization algorithms to determine the most efficient and cost-effective way to regulate energy usage and production. By applying the forecasted data, the system can anticipate future energy demand and supply, which allows for proactive decision-making to manage energy resources effectively. Optimization algorithms can be used to determine the highly effective and cost-effective process to meet power demand while minimizing costs.

The intention of the proposed system is to equalize the resources available and consumption of energy while minimizing costs as well reducing environmental impact of energy consumption, the system can prevent blackouts and other power disruptions. This might be accomplished by utilizing energy from renewable resources, reducing power wastage, adding to manage energy consumption during peak periods. Overall, a smart grid optimization system based on forecasted cost, power, and energy reflects the potential for better reliability, minimize expenditures, and enhance energy efficiency.

To head a mathematical expression for an optimization problem, there are steps that need to follow it:

a. Define the decision variables: the decision variables are the values that wanted to optimize. It needs to define explicitly

b. Formulate the objective function: is the function that we want minimized. It should institute a function of the decision variables.

c. Define the constraints: Constraints are the conditions that need to be satisfied. Constraints can be expressed as equalities or inequalities.

Put it all together: Combine the decision variables, objective function, and constraints into a mathematical expression. To reduce the overall cost of variable-priced power, the equation used is the cost function equation (1):

$$TotalCost = \sum_{i=1}^{K} GridCost(i) * GridEnergy(i) \tag{3.1}$$

Where k=24 is how many hours of times should the algorithm predicted during day

The variation of the cost depends on the energy storage system capability as in equation (2):

$$B_{energy}(i) = B_{energy}(i-1) + B_{power} * \Delta t \tag{3.2}$$

where: $B_{energy}(i)$ The initial energy of storage system ESS

Δt Time rate of initial energy3

The power scales of the proposed system is described in equation (3):

$$\sum sources\ power = \sum loads\ power \tag{3.3}$$

The linear programming optimization algorithm is used for cost optimization for many cases of renewable energy production. The main algorithm is expressed in equation (4):

$$\min(f^T x) \text{ Such that} \begin{cases} A.x \le b \\ A_{eq}.x = b_{eq} \end{cases} \tag{3.4}$$

Whereas: b is a constant value from the forecasted data represent min .value

Where: $$x = [grid_{power}(1{:}K)\ B_{power}(1{:}K)\ B_{energy}(1{:}K)]^{\mathrm{T}} \tag{3.5}$$

Which is a matrix of three values represent as: grid power, battery power and battery energy

The optimization problem constrains may be expressed as in equation (6):

$$A_{eq}.x = b_{eq} \tag{3.6}$$

Whereas both $\mathrm{A_{eq}}.,\mathrm{b_{eq}}$ Equivalent constraint as below

$$A_{eq} = \begin{bmatrix} I_{k\times k} & I_{k\times k} & 0_{k\times k} \\ 0_{k\times k} & \alpha_{k\times k} & \beta_{k\times k} \end{bmatrix} \tag{3.7}$$

$$b_{eq} = \begin{bmatrix} P_{Load}(1:k) - P_{pv}(1:k) \\ B_{energy} \\ 0 \end{bmatrix} \quad (3.8)$$

$$\alpha = \begin{bmatrix} 0 & 0 & 0 \\ \Delta T & 0 & 0 \\ 0 & \Delta T & 0 \end{bmatrix} \quad (3.9)$$

$$\beta = \begin{bmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix} \quad (3.10)$$

The cost per day for results from comparing the proposed system to conventional microgrids demonstrate the suggested algorithm performs, simulation is done for many operating cases. The proposed system Simulink model is shown in figure 3.1.

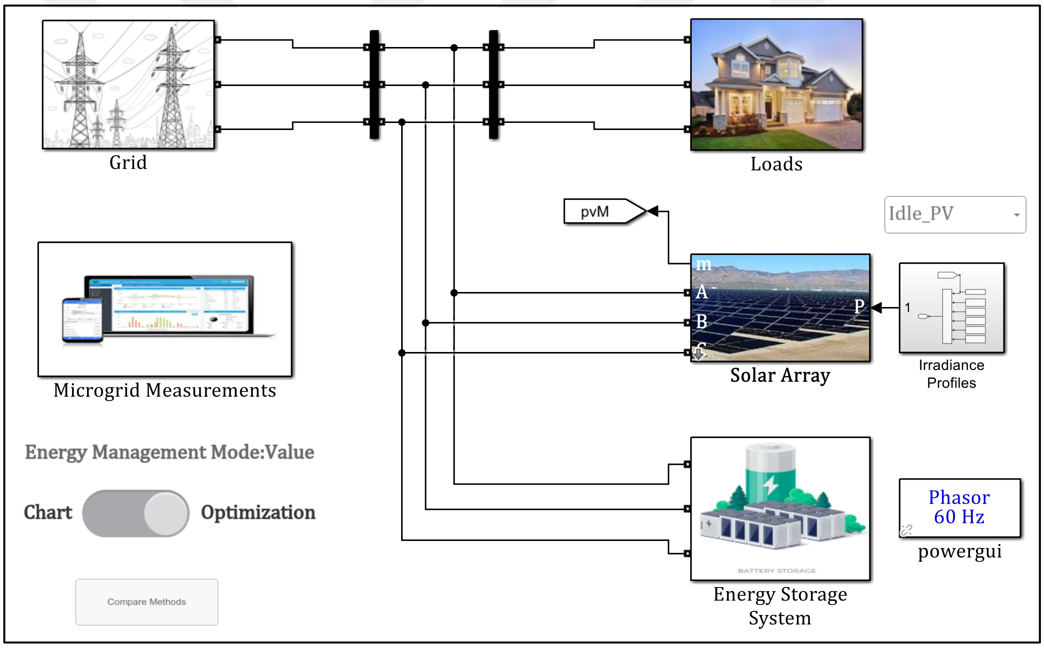

Figure 3.1: Suggested Strategy Simulink Model.

3.1 LOAD SPECIFUCATIONS

The proposed system Simulink model is shown in Figure 1. The load used in the proposed system contains two types of loads, constant inductive load and variable load. The combination of the two types of loads introduced to simulate the smart grid as near as possible to the practical grid.

a. Constant load capacity: 350 KW.

b. Variable load capacity: 200 KW maximum, the variable load varied with time.

3.2 SOLAR ARRAY

The solar array system capacity is selected to be 500 KW, grid connected. The operating modes of the photovoltaic (PV) array system covers all expected cases (idle, 200 W/m^2, 400W/m^2, 750 W/m^2, 1000W/m^2, and in variable irradiance such as in cloudy weather).

3.3 ENERGY STORAGE SYSTEM

The energy storage system rated with 400 KW with charging and discharging controller. The charging-discharging duties depends on the energy cost, load nature and renewable energy generated.

3.4 UTILITY GRID

Utility grid accept and release power connected via Alternating current (AC) generator and breaker to disconnect the grid. The utility grid contains an AC three phase’s generator, the main transformer, and the main bus. The utility grid has the ability to generate and absorb electrical energy.

4. SIMULATION RESULTS DISCUSSION

The proposed system simulated for many operating cases (depending on the load nature and renewable energy produced by the PV array). Each case illustrated depending on its conditions. The simulation is done for an optimized system and for classical operation and the results are compared for each case.

4.1 CASE 1: SYSTEM PERFORMANCE WHEN THE PV ARRAY IS IDLE

In this case the system works without renewable energy produced from the PV array. Figure 4.1 shows the system power and cost curves when the system works without optimized controller. It is clear that the energy cost per day arises with the energy price increment as in figure 4.1, and the energy storage system is charged for a short duration independent of the load capacity. While in figure 4.2 shows the same curves for the same operating condition but with the optimized controller, the cost per day curve is less than that in figure 4.1 for the same load case. The energy storage system supplied or shared the load in two intervals when the energy prices increased over the normal limit, and stores energy when the energy cost decrease to minimum value.

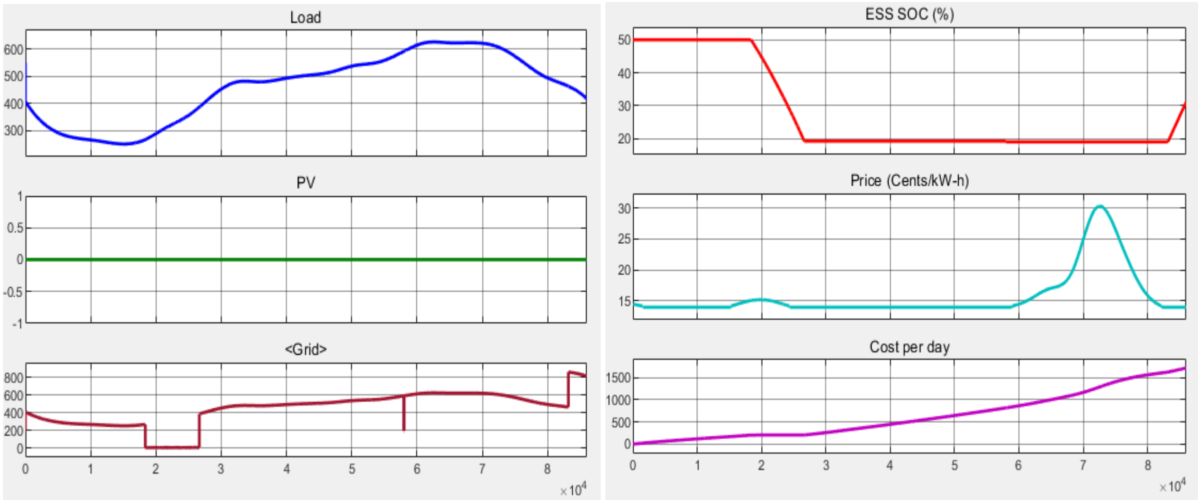

Figure 4.1: System Performance When The PV Array Is Idle Without Optimized Control.

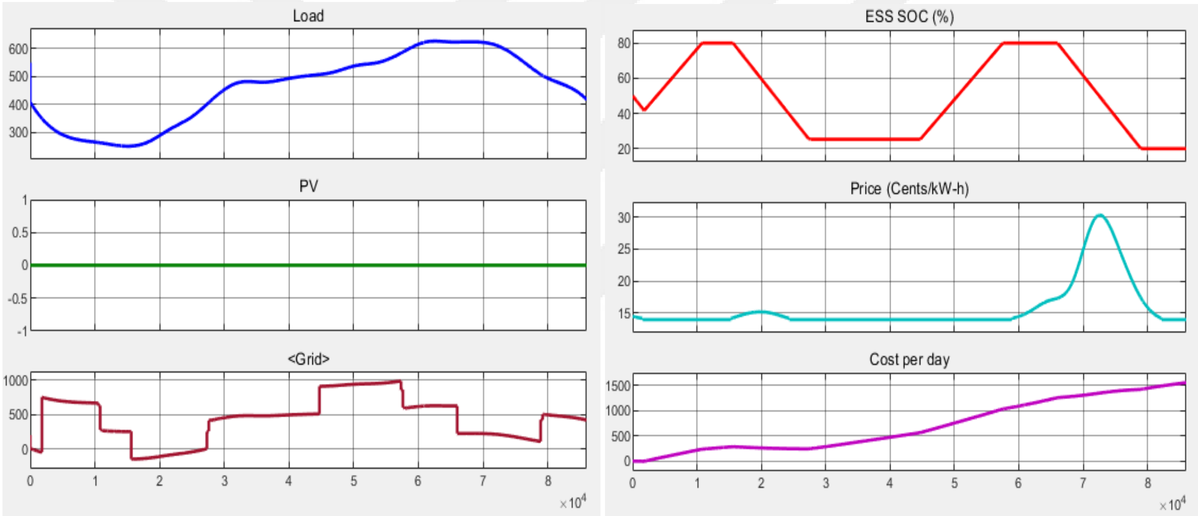

Figure 4.2: System Simulation Results In Case Without Renewable Source With Optimization.

Energy cost per day for the two operating methods are compared as in figure 4.3. The cost for an optimized system is better than the cost for a traditional system during the highest energy price duration.

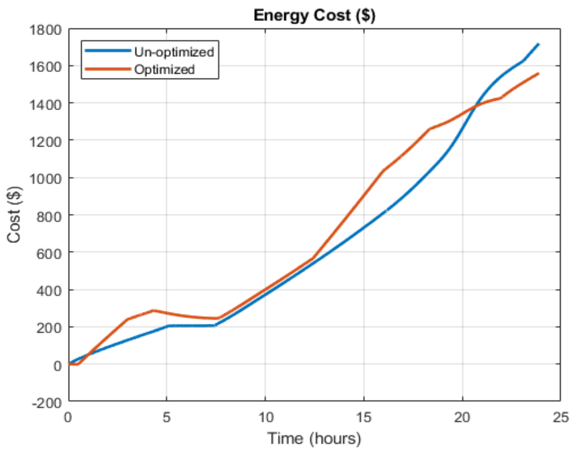

Figure 4.3: Energy Cost Comparison When The PV Array Is Idle.

4.2 CASE 2: SYSTEM SIMULATION WHEN THE SOLAR IRRADIANCE LEVEL IS 200 W/M^2

In this scenario the system power and cost curves with and without optimization are shown in figure 4.4.and 4.5 respectively. The maximum solar irradiance is 200 W/m^2. System performance without using optimized controller formulated in terms of grid power, PV array power, energy storage system and its state of charge (SOC) which represent the amount of electrical charge stored in the battery at time (t) and energy cost curves are shown.

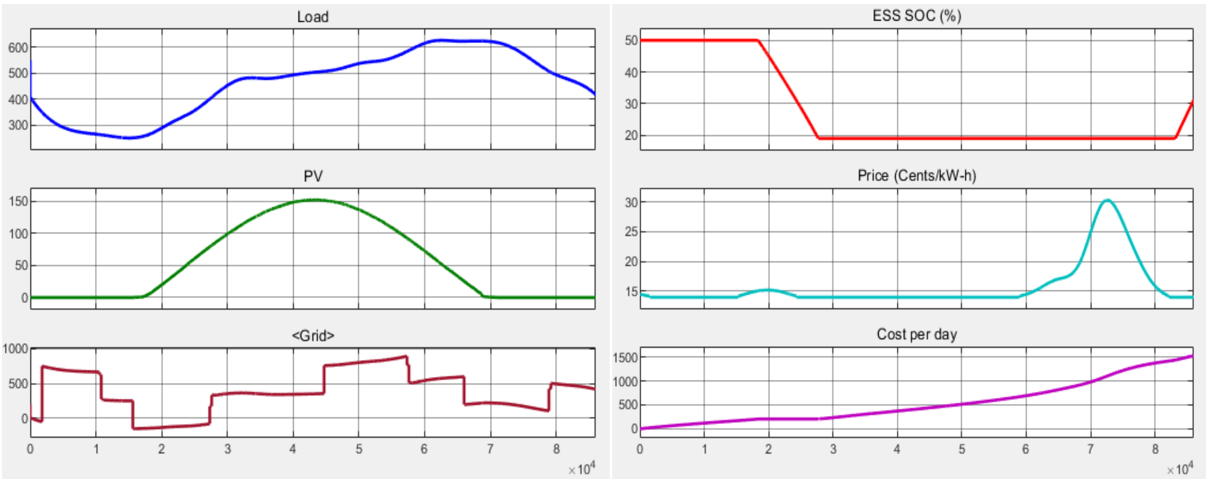

Figure 4.4: System Performance In Case Of 200 W/M2 Without Optimization

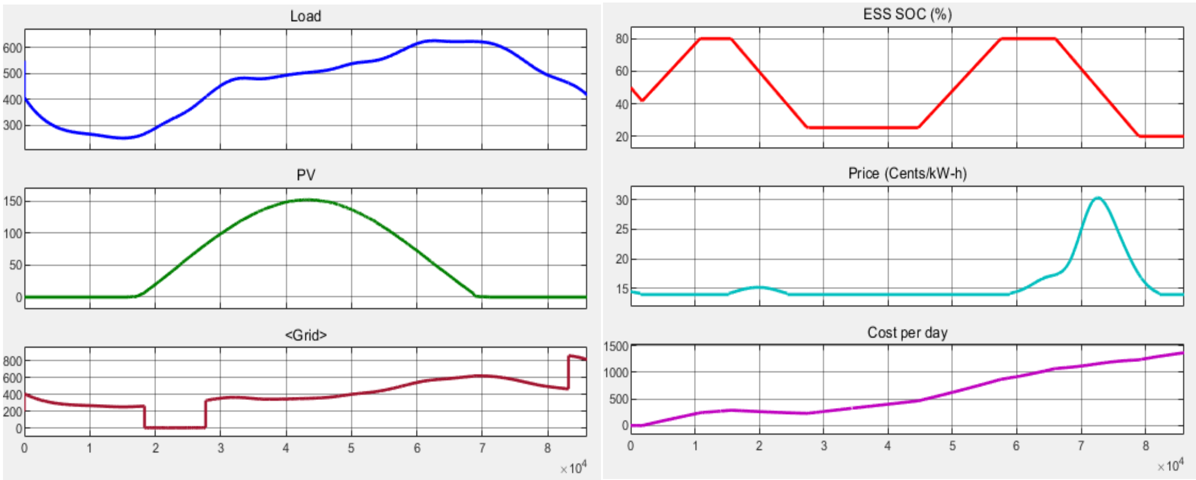

Figure 4.5: System Power and Cost Curves when the Ppv is 200 KW With Optimization.

The cost minimization and charging controlling enhancement when using optimized controller is shown in figure 4.5. The charge / discharge duration depends on power price fluctuation and the production of renewable energy. Finally, in order to be more visible in terms of visuals, Figure 6 shows the comparison between the two operating cases. The system performance in optimized and non-optimized operation modes, the effect of optimized operating on the energy cost appears in the most significant duration (when the energy cost reaches its highest limit). The red curve represents the energy cost curve for the optimized system, and it shows that the maximum energy cost for the optimized system is 1370$ while the un-optimized system energy cost reaches 1530$ for the same load conditions and renewable energy production.

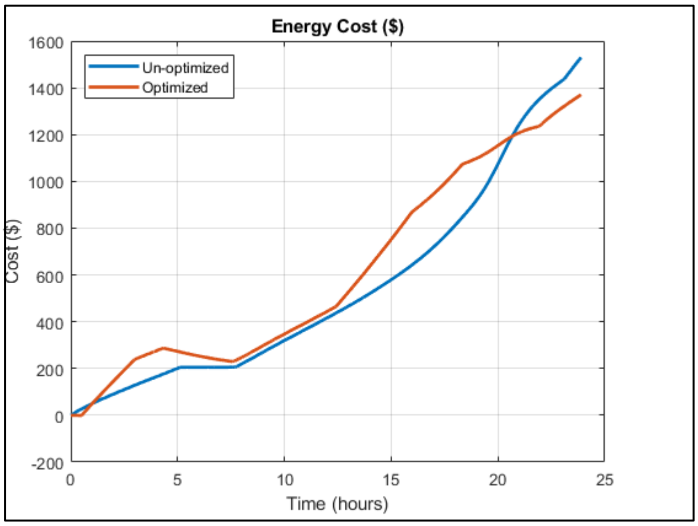

Figure 4.6: Energy Cost Comparison While The Ppv Is 200 KW.

4.3 CASE 3: SYSTEM PERFORMANCE WHEN THE SOLAR IRRADIANCE IS 400 W/M2

The effect of renewable energy increasing is clear on the grid power curve but the energy cost still high especially when the energy price increased. Figure 4.7 shows the system curves when the system works without using an optimization algorithm. The cost per day reaches 1342 $ as shown in Figure 4.7. From the grid power curve, the grid supplies the load with about 600 KW while the energy price in its maximum value. The improvement in system performance and the overall energy cost reduction when using the optimized controller are shown in Figure 4.8.

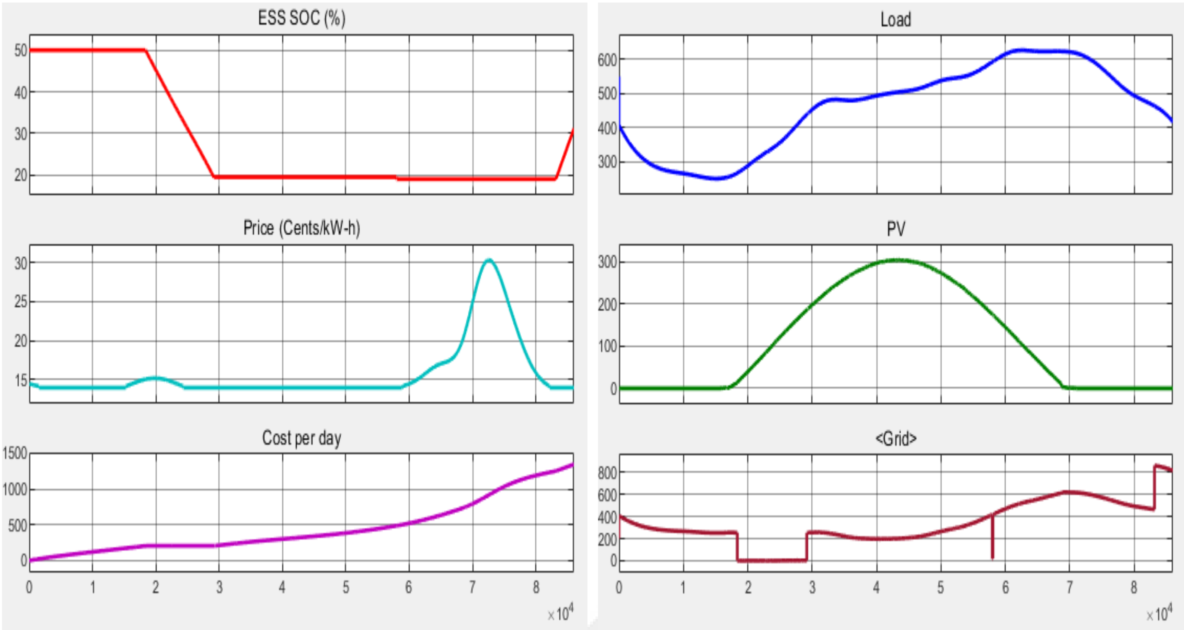

Figure 4.7: System Performance For 400 W/M^2 Without Optimization.

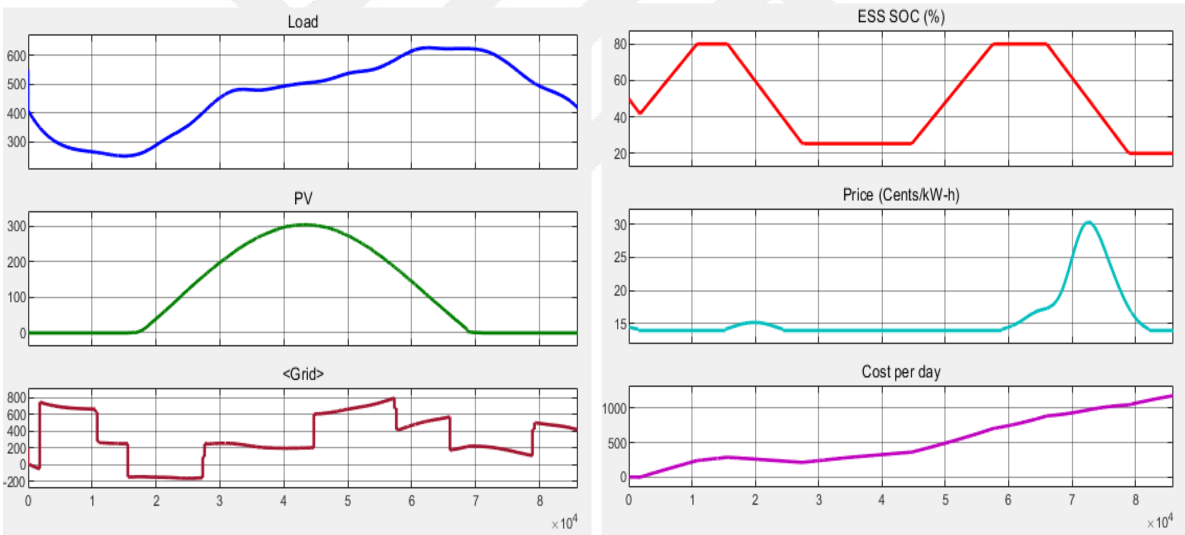

Figure 4.8: System Performance In Case Of 400 W/M^2 Using Optimization.

The cost comparison between the two operating cases is shown in figure 4.9. The performance of the optimized system is also the best in this case. The optimized system forced the energy storage system to charge during the low energy price duration and to discharge during the high energy price duration. The grid power curve shows that the grid supplies power to the load in minimum value (about 200KW) in the highest energy price duration, therefore the energy cost per day is less than that in nonoptimized operation mode.

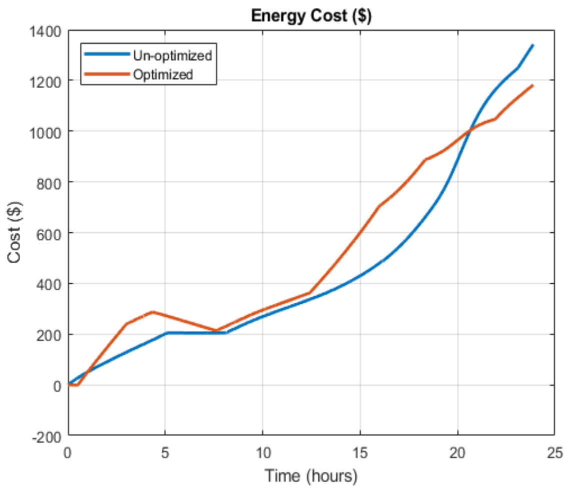

Figure 4.9: Energy Cost Comparison For The Two Operating Cases.

The variation in the energy cost curve for the optimized system as shown in Figure 9 depends on two parameters: the first one is the grid energy price and the second the renewable energy generation. The energy cost for the optimized system is lower than that of the nonoptimized system in the duration when the grid energy cost reaches its maximum limit.

4.4 CASE 4: SYSTEM SIMULATION FOR MAXIMUM SOLAR IRRADIANCE

The minimum energy cost per day achieved when the renewable energy genrated by the PV array is the maximum (when the solar irradiance level = 1000 W/m2), but the cost for a traditional system reaches a level higher thant the level whe the system simulated using the optimized controller, figures 4.10 and 4.11 show the difference in cost between the two cases.

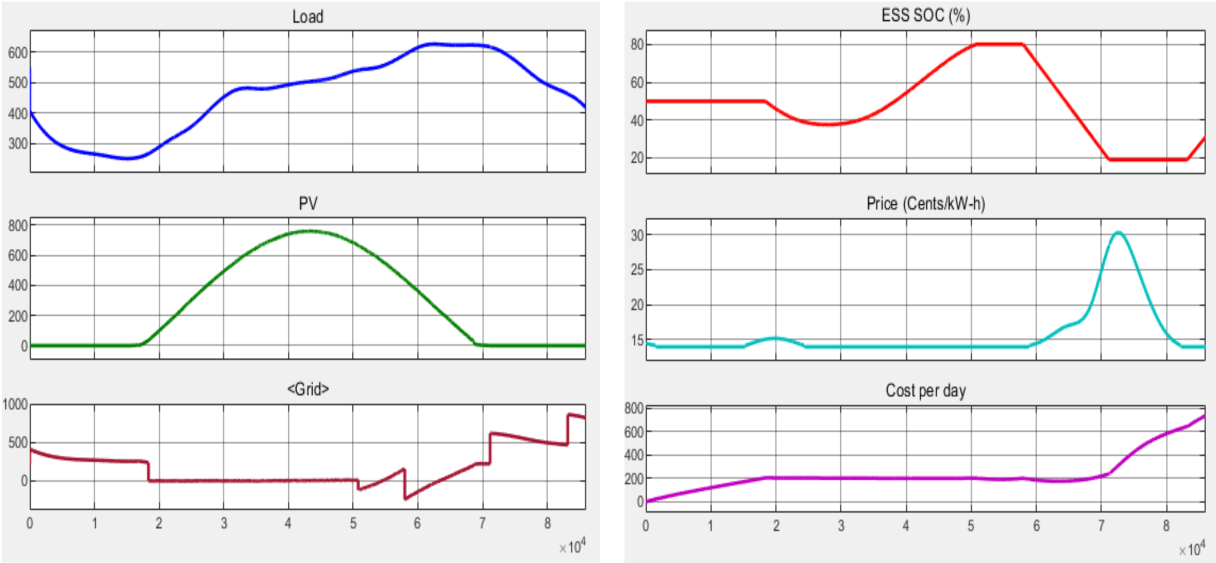

Figure 4.10: System Performance For 1000W/M2 Solar Irradiance Without Optimization.

From the grid power curve shown in Figure 10 the grid starts to supply the load when the renewable energy (PV array power) reaches zero and the energy storage system discharged, this duration is the same duration when the grid energy cost reaches its maximum value, therefore the energy cost per day for the system, in this case, start raising and become about 735.7$.

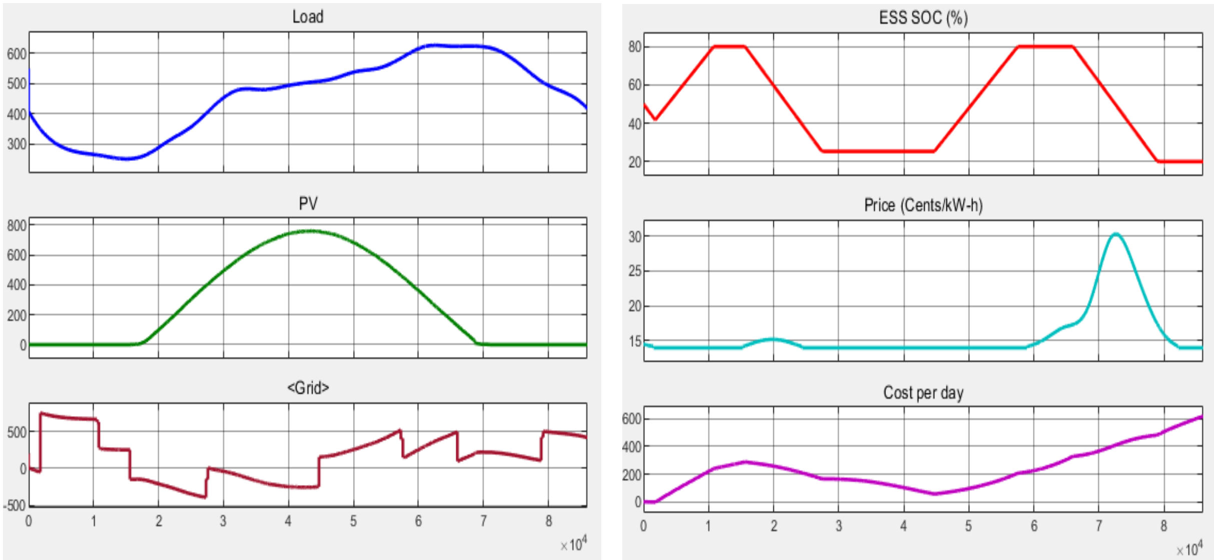

Figure 4.11: System Performance In Case Of 1000W/M^2 With Optimized Controller.

The optimized controller controls the energy storage system charging discharging intervals depends on the grid energy cost and renewable energy amount. The ESS SOC curve shown in Figure 11 shows the system performance in the optimized operating mode, which leads to cost per day reduction because the second ESS discharge interval starts when the grid energy cost starts rising. The cost per day comparison for these two cases is shown in Figure 12. It is clear that the energy cost is the best for the optimized system compared with the classical system.

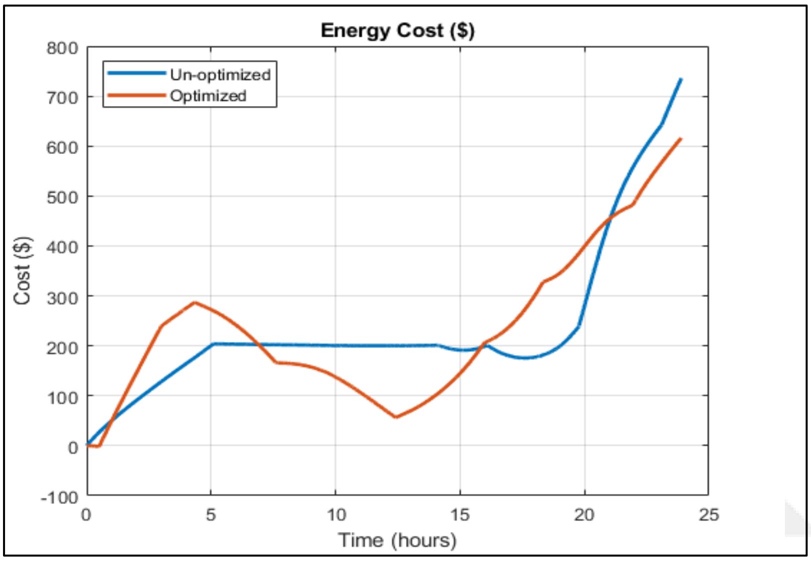

Figure 4.12: Energy Cost Comparison For The Two Operating Cases.

4.5 CASE 5: SYSTEM PERFORMANCE IN CASE OF CLOUDY WEATHER

In this case the influence of cloudy weather is taken into account. Figure 4.13 shows the system power, SOC and cost curves for the classical operation case, while figure 4.14 shows the same curves but for using the optimized controller.

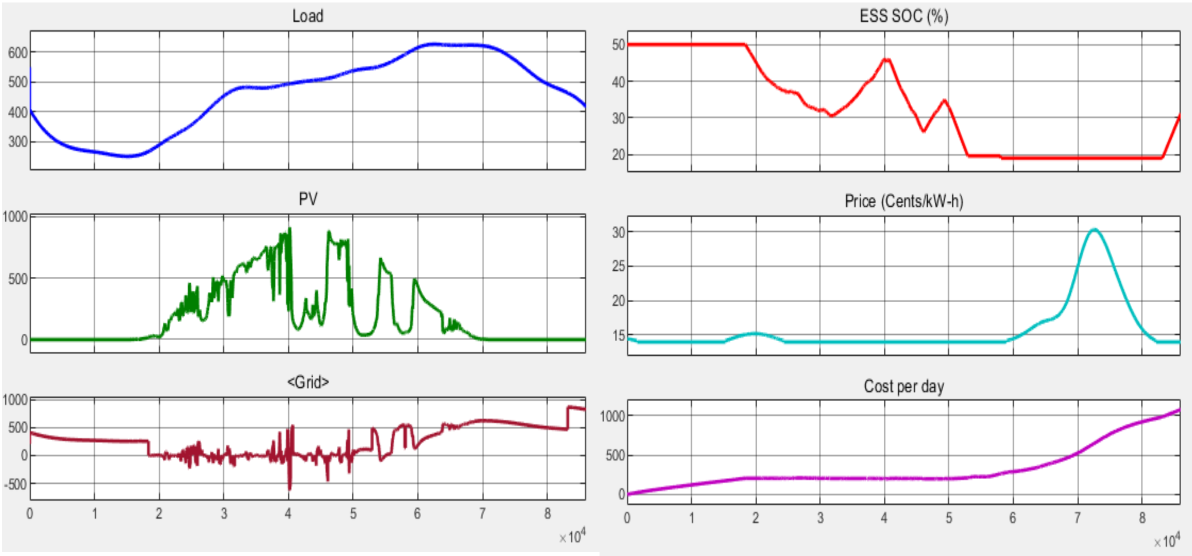

Figure 4.13: System Power, SOC, And Cost Curves For Cloudy Weather Without Optimization.

Because of the variation in renewable energy production in cloudy weather, the ESS could not reach a fully charged state and that leads to fast discharging of ESS as it is clear in the ESS SOC curve in Figure 4.13. The direct relation between ESS charging/discharging process and renewable energy production makes the grid supplies the load power when the grid energy price reaches its maximum limit. The cost per day exceeds 1073$ for these operating modes.

In an optimized system both grid energy price and renewable energy affect the ESS charging discharging duties. The cost per day is controlled to be less than 1000$ for the same conditions mentioned in nonoptimized operating mode.

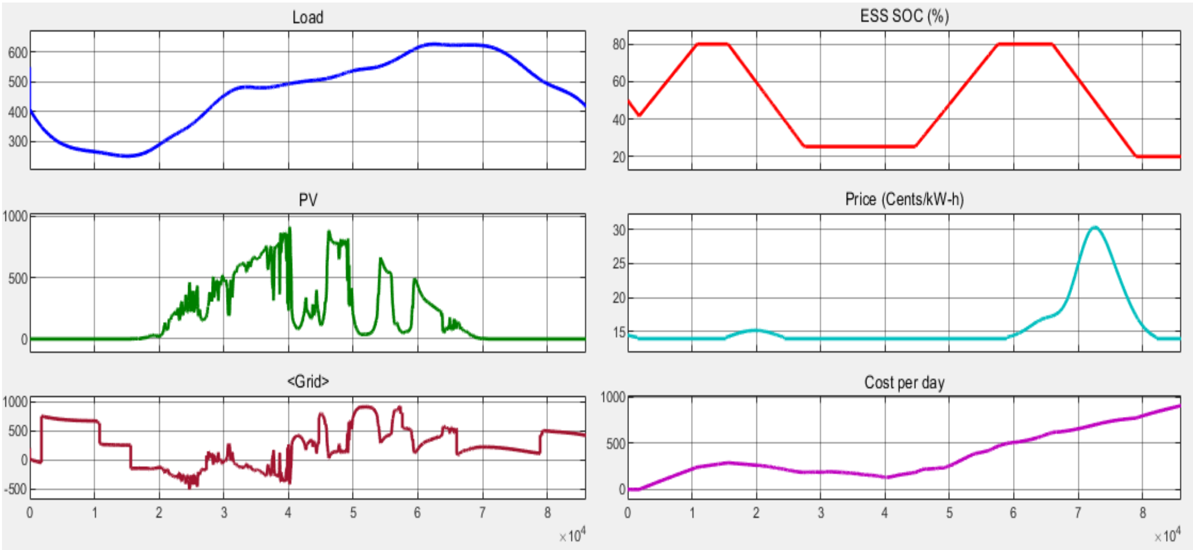

Figure 4.14: System Power, Soc And Cost Curves For Cloudy Weather Using Optimization.

The cost per day comparison for the two mentioned cases is shown in figure 4.15.

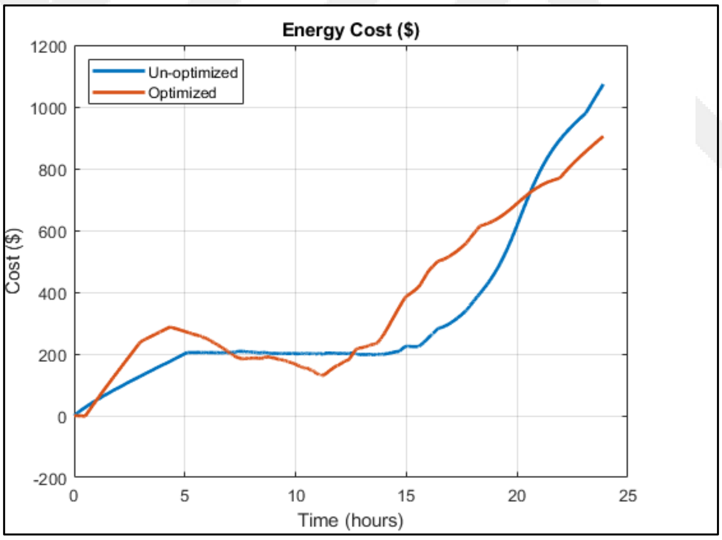

Figure 4.15: Cost Per Day Comparison For Cloudy Weather.

In all simulated cases the performance of the optimized system is the best. The cost per day is lower for the optimized system and the cost reduction reaches 15.7 % (depending on the renewable energy generation). Table 2 contains the energy cost per day for all studied cases.

Table 4.1: System Cost Per Day For All Studied Cases**.**

Case	Optimized ($)	Non-Optimized ($)	Reduction (%)
0	1558.72	1718.17	9.28 %
200	1370.32	1530.15	10.45 %
400	1181.75	1341.97	11.94 %
1000	616.2	735.7	16.24 %
cloudy	904.48	1072.99	15.7 %

5. CONCLUSIONS AND FUTURE WORKS

5.1 CONCLUSIONS

Energy management techniques play an important role in reducing costs paid to cover electric energy expenditures. The researchers presented a lot of techniques for energy management, and many of them had negative aspects, such as cancelling some loads in order to maintain low costs, changing operating times, or disconnecting them when peak states are reached. In this research paper, the suggested method for reducing electrical energy costs in a microgrid containing multiple types of loads relies on optimizing the charging and discharging of the energy storage system based on the amount of energy generated by the solar cell system and price reports for previous periods to manage energy consumption in micro-networks. This approach is innovative because it does not involve reducing the load or changing its operating periods, which can affect the production of factories and households.

Optimizing the charging and discharging of the energy storage system is crucial for reducing energy costs in micro-networks. By storing excess energy generated by the solar cell system during peak production periods and releasing it during periods of high demand, the system can balance energy supply and demand and reduce the need to utilize energy from the grid at high prices. The use of price reports for previous periods also allows for a more informed decision-making process when it comes to charging and discharging the energy storage system. By analyzing the price trends over time, the system can determine the best times to charge and discharge the energy storage system to take advantage of lower electricity prices.

Overall, the proposed method for reducing electrical energy costs in a microgrid promising and has the potential to help factories, businesses, and households save money on their electricity bills while maintaining their usual load and operating periods as compared with others using different optimization algorithms an optimal DSM program is used to optimally shift the time of shiftable loads and modify the total load of the utility, thereby reducing anticipated peak loads and accomplishing the aforementioned goals.

The cost reduction varied between 9% to 16.24% depending on the power generated by the renewable energy source.

5.2 FUTURE WORKS

Depending on the simulation results of the suggested techniques many suggestions can be proposed as future works.

a. Use the same algorithm for large scale utility grids.

b. Utilize the large-scale utility grids as storage device instead of battery-based storage devices.

c. Use another algorithm such as deep learning or machine learning for cost minimization for the same system and satisfy the results accuracy.

REFERENCES

[1] A. Pratt, D. Krishnamurthy, M. Ruth, H. Wu, M. Lunacek, and P. Vaynshenk, “Transactive home energy management systems: The impact of their proliferation on the electric grid,” *IEEE Electrif. Mag.*, vol. 4, no. 4, pp. 8–14, 2016.

[2] A. Motamedi, H. Zareipour, and W. D. Rosehart, “Electricity price and demand forecasting in smart grids,” *IEEE Trans. Smart Grid*, vol. 3, no. 2, pp. 664–674, 2012.

[3] A. Anvari-Moghaddam, H. Monsef, and A. Rahimi-Kian, “Optimal smart home energy management considering energy saving and a comfortable lifestyle,” *IEEE Trans. Smart Grid*, vol. 6, no. 1, pp. 324–332, 2014.

[4] X. Wang, Y. Zhang, G. B. Giannakis, and S. Hu, “Robust smart-grid-powered cooperative multipoint systems,” *IEEE Trans. Wirel. Commun.*, vol. 14, no. 11, pp. 6188–6199, 2015.

[5] D. C. Mazur, R. A. Entzminger, and J. A. Kay, “Enhancing traditional process SCADA and historians for industrial & commercial power systems with energy (Via IEC 61850),” in *2014 IEEE/IAS 50th Industrial & Commercial Power Systems Technical Conference*, 2014, pp. 1–7.

[6] J. Soni and S. K. Panda, “Electric spring for voltage and power stability and power factor correction,” *IEEE Trans. Ind. Appl.*, vol. 53, no. 4, pp. 3871–3879, 2017.

[7] A. Mondal, M. S. Illindala, A. S. Khalsa, D. A. Klapp, and J. H. Eto, “Design and operation of smart loads to prevent stalling in a microgrid,” *IEEE Trans. Ind. Appl.*, vol. 52, no. 2, pp. 1184–1192, 2015.

[8] S. Voronin and J. Partanen, “Price forecasting in the day-ahead energy market by an iterative method with separate normal price and price spike frameworks,” *Energies*, vol. 6, no. 11, pp. 5897–5920, 2013.

[9] R. Sharifi, S. H. Fathi, and V. Vahidinasab, “A review on Demand-side tools in electricity market,” *Renew. Sustain. Energy Rev.*, vol. 72, pp. 565–572, 2017.

[10] S.-J. Kim, “Appliance recognition unit for home energy management system with UPnP network,” *IEEE Syst. J.*, vol. 11, no. 4, pp. 2794–2803, 2015.

[11] T. Zia and U. Zahid, “Long short-term memory recurrent neural network architectures for Urdu acoustic modeling,” *Int. J. Speech Technol.*, vol. 22, pp. 21–30, 2019.

[12] D. Minoli, K. Sohraby, and B. Occhiogrosso, “IoT considerations, requirements, and

architectures for smart buildings—Energy optimization and next-generation building management systems," *IEEE Internet Things J.*, vol. 4, no. 1, pp. 269–283, 2017.

[13] W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, "Edge computing: Vision and challenges," *IEEE internet things J.*, vol. 3, no. 5, pp. 637–646, 2016.

[14] S. Wu *et al.*, "Survey on prediction algorithms in smart homes," *IEEE Internet Things J.*, vol. 4, no. 3, pp. 636–644, 2017.

[15] C. Zhao, S. Dong, F. Li, and Y. Song, "Optimal home energy management system with mixed types of loads," *CSEE J. Power Energy Syst.*, vol. 1, no. 4, pp. 29–37, 2015.

[16] B. Sivaneasan, K. N. Kumar, K. T. Tan, and P. L. So, "Preemptive demand response management for buildings," *IEEE Trans. Sustain. Energy*, vol. 6, no. 2, pp. 346–356, 2014.

[17] M. Choobineh and S. Mohagheghi, "Optimal energy management in an industrial plant using on-site generation and demand scheduling," *IEEE Trans. Ind. Appl.*, vol. 52, no. 3, pp. 1945–1952, 2015.

[18] Y. Zhou, X. Chen, A. Y. Zomaya, L. Wang, and S. Hu, "A dynamic programming algorithm for leveraging probabilistic detection of energy theft in smart home," *IEEE Trans. Emerg. Top. Comput.*, vol. 3, no. 4, pp. 502–513, 2015.

[19] S. M. Tabatabaei, S. Dick, and W. Xu, "Toward non-intrusive load monitoring via multi-label classification," *IEEE Trans. Smart Grid*, vol. 8, no. 1, pp. 26–40, 2016.

[20] S. D. J. McArthur *et al.*, "Multi-agent systems for power engineering applications—Part I: Concepts, approaches, and technical challenges," *IEEE Trans. Power Syst.*, vol. 22, no. 4, pp. 1743–1752, 2007.

[21] G. Weiss, *Multiagent systems: a modern approach to distributed artificial intelligence*. MIT press, 1999.

[22] S. K. Das, D. J. Cook, A. Battacharya, E. O. Heierman, and T.-Y. Lin, "The role of prediction algorithms in the MavHome smart home architecture," *IEEE Wirel. Commun.*, vol. 9, no. 6, pp. 77–84, 2002.

[23] W. Li, T. Logenthiran, V.-T. Phan, and W. L. Woo, "Housing development building management system (hdbms) for optimized electricity bills," *Trans. Environ. Electr. Eng.*, vol. 2, no. 2, pp. 64–71, 2017.

[24] H.-L. Chao, C.-C. Tsai, P.-A. Hsiung, and I. Chou, "Smart grid as a service: a

discussion on design issues," *Sci. World J.*, vol. 2014, 2014.

[25] S. D. Ramchurn, P. Vytelingum, A. Rogers, and N. R. Jennings, "Putting the'smarts' into the smart grid: a grand challenge for artificial intelligence," *Commun. ACM*, vol. 55, no. 4, pp. 86–97, 2012.

[26] R. R. Mohassel, A. S. Fung, F. Mohammadi, and K. Raahemifar, "A survey on advanced metering infrastructure and its application in smart grids," in *2014 IEEE 27th Canadian conference on electrical and computer engineering (CCECE)*, 2014, pp. 1–8.

[27] Y. Yoldaş, A. Önen, S. M. Muyeen, A. V Vasilakos, and I. Alan, "Enhancing smart grid with microgrids: Challenges and opportunities," *Renew. Sustain. Energy Rev.*, vol. 72, pp. 205–214, 2017.

[28] F. Corno and F. Razzak, "Intelligent energy optimization for user intelligible goals in smart home environments," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 2128–2135, 2012.

[29] B. Das, D. J. Cook, N. C. Krishnan, and M. Schmitter-Edgecombe, "One-class classification-based real-time activity error detection in smart homes," *IEEE J. Sel. Top. Signal Process.*, vol. 10, no. 5, pp. 914–923, 2016.

[30] J. M. Gillis and W. G. Morsi, "Non-intrusive load monitoring using semi-supervised machine learning and wavelet design," *IEEE Trans. Smart Grid*, vol. 8, no. 6, pp. 2648–2655, 2016.

[31] B. Mahesh, "Machine Learning Algorithms-A Review," *Int. J. Sci. Res. (IJSR).[Internet]*, vol. 9, pp. 381–386, 2020.

[32] M. J. Prince and R. M. Felder, "Inductive teaching and learning methods: Definitions, comparisons, and research bases," *J. Eng. Educ.*, vol. 95, no. 2, pp. 123–138, 2006.

[33] Akel Fethi and others "Power Control of Three Phase Single Stage Grid Connected Photovoltaic System" 2016 IEEE.

[34] Wei Yi, Dawei Y, Xiongwei Hu, Xiangnv Wang and Fang Shi. "Modeling and Simulation of DC Micro-grid Based on Virtual Motor Control" 2017 IEEE Transportation Electrification Conference and Expo, AsiaPacific (ITEC Asia-Pacific).

[35] Mahmoud Nour Ali "Improved Design of Artificial Neural Network for MPPT of Grid-Connected PV Systems" 2018 IEEE.

[36] Prashant Kumar Singh and Dr.Anil Kumar Dahiya “Analysis Modelling & Simulation of grid connected PV-System with D-Statcom” 2018 IEEE.

[37] W. Li, C. H. Ng, T. Logenthiran, V.-T. Phan, and W. L. Woo, “Smart grid distribution management system (SGDMS) for optimized electricity bills,” in *2018 IEEE Transportation Electrification Conference and Expo (ITEC)*, 2018, pp. 212–216.

[38] X. Chen, T. Wei, and S. Hu, “Uncertainty-aware household appliance scheduling considering dynamic electricity pricing in smart home,” *IEEE Trans. Smart Grid*, vol. 4, no. 2, pp. 932–941, 2013.

[39] Jasim, A.M.; Jasim, B.H.; Neagu, B.-C.; Alhasnawi, B.N. Efficient Optimization Algorithm-Based Demand-Side Management Program for Smart Grid Residential Load. Axioms 2023, 12, 33. https://doi.org/10.3390/ axioms12010033.

[40] Kantarci, M.; Mouftah, H. Wireless Sensor Networks for Cost-Efficient Residential Energy Management in the Smart Grid”. IEEE Trans. Smart Grid 2011, 2, 314–325. [CrossRef]

[41] Zhu, Z.; Tang, J.; Lambotharan, S.; Chin, W.H.; Fan, Z. An Integer Linear Programming Based Optimization for Home DemandSide Management in Smart Grid. In Proceedings of the IEEE PES Innovative Smart Grid Technologies (ISGT), Washington, DC, USA, 16–20 January 2012; pp. 1–5. [CrossRef]

[42] M. A. A. Pedrasa, T. D. Spooner, and I. F. MacGill, “Coordinated scheduling of residential distributed energy resources to optimize smart home energy services,” *IEEE Trans. Smart Grid*, vol. 1, no. 2, pp. 134–143, 2010.

[43] T. M. Hansen, E. K. P. Chong, S. Suryanarayanan, A. A. Maciejewski, and H. J. Siegel, “A partially observable markov decision process approach to residential home energy management,” *IEEE Trans. Smart Grid*, vol. 9, no. 2, pp. 1271–1281, 2016.

[44] J. M. Angarita and J. G. Usaola, “Combining hydro-generation and wind energy: Biddings and operation on electricity spot markets,” *Electr. Power Syst. Res.*, vol. 77, no. 5–6, pp. 393–400, 2007.

[45] K. Maciejowska and R. Weron, “Short-and mid-term forecasting of baseload electricity prices in the UK: The impact of intra-day price relationships and market fundamentals,” *IEEE Trans. power Syst.*, vol. 31, no. 2, pp. 994–1005, 2015.

[46] F. H. Al-Qahtani and S. F. Crone, “Multivariate k-nearest neighbour regression for time series data—A novel algorithm for forecasting UK electricity demand,” in *The*

2013 international joint conference on neural networks (IJCNN), 2013, pp. 1–8.

[47] J. H. Roh, M. Shahidehpour, and L. Wu, “Market-based generation and transmission planning with uncertainties,” *IEEE Trans. Power Syst.*, vol. 24, no. 3, pp. 1587–1598, 2009.

[48] S. Kumar, V. Pavithra, R. Banu, and G. Supriya, “Smart Home Energy Management System Including Renewable Energy Based on Zigbee and ARM9 Microcontroller,” *Asian J. Appl. Sci. Technol.*, vol. 1, no. 2, pp. 240–244, 2017.

[49] S. Zhang, J. Yang, X. Wu, and R. Zhu, “Dynamic power provisioning for cost minimization in islanding micro-grid with renewable energy,” in *ISGT 2014*, 2014, pp. 1–5.

[50] Y.-H. Lin and M.-S. Tsai, “An advanced home energy management system facilitated by nonintrusive load monitoring with automated multiobjective power scheduling,” *IEEE Trans. Smart Grid*, vol. 6, no. 4, pp. 1839–1851, 2015.

[51] I.-Y. Joo and D.-H. Choi, “Distributed optimization framework for energy management of multiple smart homes with distributed energy resources,” *Ieee Access*, vol. 5, pp. 15551–15560, 2017.

[52] T. Logenthiran, D. Srinivasan, A. M. Khambadkone, and H. N. Aung, “Multiagent system for real-time operation of a microgrid in real-time digital simulator,” *IEEE Trans. Smart Grid*, vol. 3, no. 2, pp. 925–933, 2012.

[53] C. Wang, Y. Zhou, B. Jiao, Y. Wang, W. Liu, and D. Wang, “Robust optimization for load scheduling of a smart home with photovoltaic system,” *Energy Convers. Manag.*, vol. 102, pp. 247–257, 2015.

[54] F. C. Schweppe, B. Daryanian, and R. D. Tabors, “Algorithms for a spot price responding residential load controller,” *IEEE Trans. Power Syst.*, vol. 4, no. 2, pp. 507–516, 1989.

[55] S. Kahrobaee, S. Asgarpoor, and W. Qiao, “Optimum sizing of distributed generation and storage capacity in smart households,” IEEE Transactions on Smart Grid, vol. 4, no. 4, pp. 1791–1801, 2013.

[56] P. Denholm and R. M. Margolis, “Evaluating the limits of solar photovoltaics (pv) in traditional electric power systems,” Energy policy, vol. 35, no. 5, pp. 2852–2861, 2007.

[57] E. Hau, *Wind turbines: fundamentals, technologies, application, economics*. Springer

Science & Business Media, 2013.

[58] F. O. Rourke, F. Boyle, and A. Reynolds, “Tidal energy update 2009,” *Appl. Energy*, vol. 87, no. 2, pp. 398–409, 2010.

[59] V. Pilloni, A. Floris, A. Meloni, and L. Atzori, “Smart Home Energy Management Including Renewable Sources: A QoE-Driven Approach,” *IEEE Trans. Smart Grid*, vol. 9, no. 3, pp. 2006–2018, 2018, doi: 10.1109/TSG.2016.2605182.

[60] N. Javaid *et al.*, “An intelligent load management system with renewable energy integration for smart homes,” *IEEE access*, vol. 5, pp. 13587–13600, 2017.

[61] F. Y. Melhem, O. Grunder, Z. Hammoudan, and N. Moubayed, “Optimization and energy management in smart home considering photovoltaic, wind, and battery storage system with integration of electric vehicles,” *Can. J. Electr. Comput. Eng.*, vol. 40, no. 2, pp. 128–138, 2017.

[62] Z. Wu, X.-P. Zhang, J. Brandt, S.-Y. Zhou, and L. I. Jia-Ning, “Three control approaches for optimized energy flow with home energy management system,” *IEEE Power Energy Technol. Syst. J.*, vol. 2, no. 1, pp. 21–31, 2015.

[63] R. Matsuo and H. Miwa, “Grid-connected electric-power control algorithm for promoting the introduction of renewable energy,” in *2014 International Conference on Intelligent Networking and Collaborative Systems*, 2014, pp. 163–168.

[64] S. Kirmani, M. Jamil, and I. Akhtar, “Bi-directional power control mechanism for a microgrid hybrid energy system with power quality enhancement capabilities,” *Int. J. Renew. energy Res.*, vol. 7, no. 4, pp. 1962–1969, 2017.

[65] X. Chen, T. Wei, and S. Hu, “Uncertainty-aware household appliance scheduling considering dynamic electricity pricing in smart home,” IEEE Transactions on Smart Grid, vol. 4, no. 2, pp. 932–941, 2013.

[66] A. Di Giorgio and L. Pimpinella, “An event driven smart home controller enabling consumer economic saving and automated demand side management,” *Appl. Energy*, vol. 96, pp. 92–103, 2012.

[67] A. Khalid, N. Javaid, M. Guizani, M. Alhussein, K. Aurangzeb, and M. Ilahi, “Towards dynamic coordination among home appliances using multi-objective energy optimization for demand side management in smart buildings,” Ieee Access, vol. 6, pp. 19 509–19 529, 2018..

[68] B. F. Hobbs and S. S. Oren, “Three waves of US reforms: Following the path of wholesale electricity market restructuring,” *IEEE Power Energy Mag.*, vol. 17, no. 1, pp. 73–81, 2019

[69] E. Rosenberg, A. Lind, and K. A. Espegren, “The impact of future energy demand on renewable energy production–Case of Norway,” Energy, vol. 61, pp. 419–431, 2013.

[70] J. Wu and N. K. Tran, “Application of blockchain technology in sustainable energy systems: An overview,” Sustainability, vol. 10, no. 9, p. 3067, 2018.

[71] P. H. J. Nardelli et al., “Energy internet via packetized management: Enabling technologies and deployment challenges,” IEEE Access, vol. 7, pp. 16909–16924, 2019.