ABSTRACT

The "Smart Home Energy Insights" project explores how various factors influence energy consumption in modern homes, aiming to optimize energy use and promote sustainability. Using a detailed dataset of household appliances like HVAC systems, lighting, and kitchen devices, along with environmental data such as temperature and humidity, the project seeks to uncover key trends in energy usage.

The project focuses on analyzing daily and seasonal energy consumption patterns, investigating how factors like weather conditions and occupant behavior affect energy demand. Advanced statistical methods and predictive models, including machine learning techniques, are used to forecast future energy usage and identify periods of high demand. Additionally, by analyzing anomalies in energy consumption—such as unexpected spikes due to malfunctioning appliances—the project helps optimize energy usage and reduce inefficiencies.

One of the core goals of the project is to enhance smart home automation. Real-time data integration allows automated systems to dynamically adjust settings based on energy consumption trends. For example, HVAC systems can optimize temperatures by considering weather conditions, and smart lighting can reduce energy waste by powering down when not needed. The ability to shift energy-intensive tasks, like running appliances, to off-peak times helps lower costs and ease the strain on the power grid.

The findings of this study have broader implications for smart home design, providing actionable insights for homeowners to manage energy consumption more effectively. By promoting energy efficiency and sustainable living practices, the project contributes to the development of eco-friendly homes. On a larger scale, it supports sustainable urban development by enabling energy-efficient communities and reducing environmental impact. The "Smart Home Energy Insights" project represents a significant step toward smarter, more energy-conscious homes and cities.

On a larger scale, the project has the potential to significantly impact energy management across residential communities, contributing to smarter, greener cities. By leveraging its predictive capabilities, utility companies and grid operators can better manage electricity supply, balance loads, and optimize energy distribution. This contributes to more sustainable energy practices at a societal level, helping reduce the strain on natural resources and limiting environmental impact.

Ultimately, the "Smart Home Energy Insights" project represents a key step toward realizing the vision of energy-efficient, self-regulating smart homes. It fosters a future where technology and sustainability go hand in hand, enabling households to enjoy the convenience of automation while actively contributing to a greener planet. Through innovation and data-driven insights, the project supports a transition to more energy-efficient homes and a more sustainable lifestyle for all.

1. Introduction

The rise of **smart homes** marks a transformative shift in how we interact with our living spaces, offering unprecedented control, convenience, and efficiency in energy management. By harnessing interconnected devices and sensors, smart homes allow for real-time monitoring and optimization of energy usage, which enhances convenience, reduces costs, improves security, and contributes to sustainability. At the heart of these advancements is the collection and analysis of extensive data, enabling homeowners and researchers to gain insights into energy consumption patterns, detect inefficiencies, and develop strategies for smarter energy use. A comprehensive dataset, consisting of **503,911 entries and 25 distinct columns**, provides a detailed snapshot of energy consumption in a typical smart home. The data captures the power usage of various household appliances, environmental conditions, and even solar power generation. By analyzing power consumption in **kilowatts (kW)** for appliances such as dishwashers, furnaces, and refrigerators, one can identify peak energy usage periods and explore opportunities to shift high-demand activities to off-peak hours. This practice not only reduces electricity costs but also alleviates the load on the energy grid, contributing to broader environmental goals. The dataset includes **solar panel data**, an essential component for understanding the integration of renewable energy sources into the home's power system. By analyzing the correlation between solar energy production and household energy consumption, homeowners can maximize the use of solar power, improving energy balance and sustainability. For instance, aligning high-energy activities with peak solar production can reduce reliance on non-renewable energy sources, thereby lowering the home's carbon footprint. Additionally, **environmental factors** such as temperature, humidity, and wind speed significantly influence energy usage. These factors affect the performance of heating, ventilation, and air conditioning (HVAC) systems, which are often the largest energy consumers in a home. Understanding the relationship between environmental conditions and energy consumption is key to enhancing energy efficiency, allowing smart homes to automatically adjust HVAC settings to optimize performance and reduce waste. The potential applications of this dataset are vast. By applying **machine learning algorithms** such as Linear Regression and Random Forest Regressor models, energy consumption patterns can be predicted based on appliance usage and environmental data. These models help in developing strategies for **predictive energy optimization**, ensuring that energy is consumed more efficiently throughout the day. Predictive maintenance of appliances, behavioral insights for energy-saving habits, and **smart grid integration** are other areas where this data can drive innovation. On a larger scale, the insights gained from such datasets have broader implications for **energy policy and sustainability efforts**. By improving energy efficiency at the household level, smart homes contribute to global sustainability goals, helping reduce carbon emissions and promoting the transition to renewable energy sources. In this way, smart homes not only offer enhanced convenience but also play a crucial role in advancing environmental objectives and fostering a greener, more energy-conscious future.

1.1 System Requirements

1.1.1 Hardware Requirements:

1. Processor: Intel Core i5 or higher (or equivalent AMD processor)

   Recommended: Intel Core i7 or AMD Ryzen 7

2. RAM: 8 GB minimum

   Recommended: 16 GB or higher

3. Storage: At least 20 GB of free space for data storage and processing

   Recommended: SSD with 50 GB or more free space for faster data processing

4. GPU: Integrated GPU is sufficient for smaller datasets

   Recommended: NVIDIA GPU with CUDA support (e.g., NVIDIA GTX 1060 or higher) for faster training times

5. Operating System: Windows 10/11, macOS 10.15 or higher, or Linux (Ubuntu 18.04 or higher)

1.1.2 Software Requirements:

1. Operating System: Windows 10/11

   macOS 10.15 or higher

   Linux (Ubuntu 18.04 or higher)

2. Programming Language:

   Python 3.8 or higher, excel

3. Development Environment:

   Google collab, spyder

5. Data Sources:

   Access to datasets, preferably in CSV or other structured format, containing household energy consumption, appliance specific power usage, and relevant weather data.

2. SYSTEM STUDY

This study is highly relevant as it addresses key issues in energy efficiency, sustainability, and cost reduction by predicting household energy consumption. Accurate predictions enable households to optimize their energy usage, reduce costs, and minimize environmental impact, while utility companies benefit from improved demand management and grid stability, ensuring a more reliable energy supply. The research also supports the advancement of smart home technologies, which can automate energy savings, and informs policymakers in developing strategies for sustainable energy planning. The scope of this study includes developing and implementing machine learning models, particularly neural networks, to predict household energy consumption based on historical data and factors such as weather, occupancy, and appliance usage. It encompasses dataset selection, data preprocessing, model training, validation, performance evaluation, and the exploration of different model architectures, feature selection techniques, and hyperparameter tuning for optimal accuracy. Additionally, the research investigates the application of these predictions in smart home systems, energy management solutions, and demand response programs, ultimately contributing to energy efficiency and sustainability initiatives by bridging the gap between academic research and practical application.

2.1 REVIEW OF LITERATURE

A. ZIPPERER, P. A. ALOISE-YOUNG, S. SURYANARAYANAN, AND D. ZIMMERLE, R. ROCHE, L. EARLE AND D. CHRISTENSEN, P. BAULEO[2013] studied Smart homes hold the potential for increasing energy efficiency, decreasing costs of energy use, decreasing the carbon footprint by including renewable resources, and trans forming the role of the occupant. At the crux of the smart home is an efficient electric energy management system that is enabled by emerging technologies in the electricity grid and consumer electronics. This article presents a discussion of the state-of-the art in electricity management in smart homes, the various enabling technologies that will accelerate this concept, and topics around consumer behavior with respect to energy usage.

ABU GUNMI MOHAMMAD A, FEIHU HU A, DIANA ABU-GHUNMI B, LINA ABU-GHUNMI C[2024] studied smart home energy management system methodology (SHEMS) to incorporate in techno-economic optimal sizing (TEOS) of residential standalone microgrid (RSMG). The SHEMS approach is based on the state of charge of battery, supercapacitor and hydrogen tank as well as day-ahead forecast of solar irradiation, wind speed and household load. Fuzzy logic decision making technique is the core of the SHEMS strategy for deciding power-side operation mode (power source selection) and demand-side consumption mode (appliances and electrolyzer operation strategies) of the RSMG. Minimizing hydrogen consumption and battery usage are considered in the SHEMS strategy. The RSMG consists of photovoltaic (PV) and wind turbine (WT) as the main power source while the backup source is formed by supercapacitor (SC), battery (Ba), fuel cell (FC), electrolyzer (El) and hydrogen tank (HT). The optimization model uses total net present value of costs (NPC) as the objective function. The considered residential household load profile consists of ten appliances, classified into four consumption categories (shiftable, adjustable, curtailable and critical) and applied to four different occupancy patterns (four classes), in addition to electrolyzer unit. The day-ahead prediction is obtained for hourly power generation and consumption using SVM-PSO model. The results, which are compared with previous researches, indicate the effectiveness of the proposed strategy to minimize the cost of the zero-emission power system balancing among cost effectiveness, technical feasibility and residents' comfort. The simulation is performed under Amman weather conditions using GAMS-MATLAB-Excel platform.

ADAMZIPPERER, PATRICIA A. ALOISE-YOUNG, SIDDHARTH SURYANARAYANAN, ROBIN ROCHE, LIEKO EARLE, DANE CHRISTENSEN, PABLO BAULEO, DANIEL ZIMMERLE[2013] studied smart homes hold the potential for increasing energy efficiency, decreasing costs of energy use, decreasing the carbon footprint by including renewable resources, and transforming the role of the occupant. At the crux of the smart homeis anefficient electric energy management system that is enabled by emerging technologies in the electricity grid and consumer electronics. This paper presents a discussion of the state of the art in electricity management in smart homes, the various enabling technologies that will accelerate this concept, and topics around consumer behavior with respect to energy usage

ALI RAZA , LI JINGZHAO , YAZEED GHADI , MUHAMMAD ADNAN , MANSOOR ALI[2024] studied electricity is establishing ground as a means of energy, and its proportion will continue to rise in the next generations. Home energy usage is expected to increase by more than 40% in the next 20 years. Therefore, to compensate for demand requirements, proper planning and strategies are needed to improve home energy management systems (HEMs). One of the crucial aspects of HEMS are proper load forecasting and scheduling of energy utilization. Energy management systems depend heavily on precise forecasting and scheduling. Consid ering this scenario, this article was divided into two parts. Firstly, this article gives a thorough analysis of forecasting models in HEMs with the primary goal of determining whichever model is most appropriate in a given situation. Moreover, for optimal utilization of scheduling strategies in HEMs, the current literature has discussed a number of scheduling optimization approaches. Therefore, secondly in this article, these approaches will be examined thoroughly to develop effective operating scheduling and to make wise judgments regarding.

BEHZAD LASHKARI, YUXIANG CHEN, AND PETR MUSILEK[2019] studied Smart home is a concept that aims to enhance the comfort of residents and facilitate household activities. The smart home is an application of ubiquitous computing which can provide the user with context-aware automated or assistive services in the form of ambient intelligence, remote control of home appliances, or automation. Smart homes attempt to integrate smartness into homes to guarantee the residents' convenience, safety, and security, while conserving the energy. The capabilities of a smart home in the context of di erent applications, have been scrutinized for this investigation. Di erent proposed architectures, protocols, and infrastructures have been taken into consideration. As the data management process is a vital part of a smart home system, many procedures of data collection, storage, and analysis have been surveyed. Methods of data acquisition has also been discussed. Existing challenges, pros, and cons of proposed schemes along with future perspectives of smart homes are identified in this report, which is intended to promote future research directions.

BILAL MUBDIR, ASAAD AL-HINDAWI, IRAQ NOOR HADI[2016] studied The rapid change and development in human life, information technology, and the increase in using home gadgets, modern appliances, and electric cars, leads to more dependency on electrical resources and consecutive increase in CO2 emission from generation plant. The current world issue is on how to save the energy by reducing the consumption and decreasing global warming. In this research, Smart Home Energy Management System (SHEMS) has been developed to operate home appliances in an optimum approach. It is aimed at reducing the consumption energy by detecting the residents' activity and identifying it among three states: Active, Away, or Sleep. The SHEMS is designed with an algorithm that is based on Hidden Markov Model (HMM) in order to estimate the probability of the home being in each of the above states. The proposed system uses the WiFi technology for data transmission inside home and the GSM technology for external communication. The proposed system and its algorithm was successfully tested and 18% of energy saving were obtained.

D LINGARAJA, S PRAVEEN KUMAR, T ARAVIND, T K SRINIVASAN, G DINESH RAM, S RAMYA[2023] studied that People are becoming more interested in the concept of creating a smart house without disrupting their power supply. This research study has designed and examined the construction of a solar cell by considering the varying intensities of light and different thickness of the p-n junction layer. Utilizing COMSOL Multiphysics for modeling. Analyses were done on the crucial factors electric field, electric potential, hole concentration, and electron concentration. The results of the simulation demonstrate that the junction thickness and intensity play a major role in the successful implementation of a solar cell. Hole and electron concentration is highly dependent on the light intensity falling on the air medium.

DR. S. G. KANADE AND ASHA K. BHISE[2022] studied countries are faced with an unreliable electric power supply to homes and the industry due to insufficient supply from the utility, causing load shedding. With the power utilities struggling to keep the lights on, there are initiatives to invest in backup power solutions and home energy management systems (HEMS) to manage this development. This paper analyzes energy consumption with the existing infrastructure of typical equipment used in homes. An approach called smart home energy management systems (SHEMS) is implemented to balance the power demand and the supply more effectively throughout the smart micro-grid by utilizing control algorithms simulated using MATLAB Simulink. This is achieved by utilizing real data from a home with commercial and residential load features in an urban area. The SHEMS revealed greater management and efficiency in electric power savings by reducing the utilities power demand. The framework adopts a local information management terminal as the core of data storage and scheduling in the home. Based on the timely purchase of electricity from the grid and the generation of electricity in combination with PV systems, an optimized simulation model for the scheduling of a new home energy management system is established. In addition, the application prospects of artificial intelligence in the HEMS are overviewed.

EUNG-SUK PARK, BYUNGYONG HWANG, KYUNGWAN KO AND DAECHEOL KIM[2017] studied The purpose of this paper is to study consumer acceptance of the Home Energy Management System, which is the next generation electronic management system that the Korean government plans to implement in households. The Home Energy Management System is a critical device in maximizing the efficiency of electric energy consumption for each household by using a smart grid. Because it can visualize real-time price information on the electricity, households can easily monitor and control the amount of electricity consumption. With this feature, the Home Energy ManagementSystemcancontributetoconsumers'totalenergysavings. Thisisamajorreasonwhythe Korean government wishes to implement it nationwide. Since the Home Energy Management System is a product that applies new technology that has not yet been directly encountered by consumers, there may be a difference in the level of public perception of the Home Energy Management System. Therefore, the impact of consumers' awareness of the Home Energy Management System on their intention to use is important. To do this, the Technology Acceptance Model is utilized in this study. Traditional research on the Technology Acceptance Model includes awareness of usefulness and ease of use as well as intention to use. In contrast, in this research, an extended Technology Acceptance Model with four additional factors—economic benefit, social contribution, environmental responsibility, and innovativeness—that may affect the consumer's awareness of usefulness and ease of use, is proposed. To collect the data, the survey was conducted with 287 respondents. As a result, the proposed model proved to be suitable in explaining the intention to use with a 70.3% explanation power. It is found that economic benefit (0.231) and innovativeness (0.259) impact on usefulness of the Home Energy Management System. Moreover, usefulness (0.551) has a bigger effect on intention to use than ease of use (0.338) does. Based on this, it is desirable for the Korean government to pursue a public relations strategy that emphasizes the economic benefits, social contributions, and environmental responsibility that will be gained when introducing the Home Energy Management System. It is effective to focus on consumers who are inclined to accept innovation. In addition, more effective results can be obtained by referring to the usefulness of the HomeEnergy Management System rather than referring to ease of use.

HEBA YOUSSEF , SALAH KAMEL & MOHAMED H. HASSAN[2023] studied This paper proposes a plan to manage energy consumption in residential areas using the demand response method, which allows electricity users to contribute to the reliability of the power system by controlling their usage. Due to the growing population, the residential sector consumes a significant amount of energy, and the objectives of this study are to lower electricity costs and the peak to average ratio, as well as reduce the amount of imported electricity from the grid. The study aims to maximize profit by properly utilizing renewable energy sources and addressing energy trading. The manta ray foraging optimization (MRFO) and long term memory MRFO (LMMRFO) algorithms are used to solve this problem. Firstly, the validation of the proposed LMMRFO technique is confirmed by seven benchmark functions and compared its results with the results of the well-known optimization algorithms including hunter prey optimization, gorilla troops optimizer, beluga whale optimization, and the original MRFO algorithm. Then, the performance of the LMMRFO is checked on the optimization of smart home energy management. In the suggested approach, a smart home decides whether to purchase or sell electricity from the commercial grid based on the cost, demand, and production of electricity from its own microgrid, which consists of a wind turbine and solar panels. Energy storage systems support the stable and dependable functioning of the power system since the solar panel and wind turbine only occasionally produce electricity. Through various case studies, the proposed plan is tested and found to be effective in reducing electricity costs and the peak to average ratio while maximizing profit. Furthermore, a comparative study is conducted to demonstrate the legality and effectiveness of LMMRFO and MRFO

LAURA FIORINI AND MARCO AIELLO[2022] studied Residential and commercial buildings are responsible for approximately 35% of carbon emissions in industrialized countries. Making buildings more efficient and sustainable is, therefore, a fundamental step toward a low-carbon energy society. A key to achiev ing sustainability is by leveraging on energy storage systems and smart technologies to switch between energy carriers in order to optimize environmental impact. However, the research on energy management in buildings has mostly focused on its economic aspect, overlooking the environmental dimension. Additionally, the concept of energy system flexibility has been mostly proposed as the ability to shift demand over time or, at most, to curtail it, aiming at reducing the system's operating costs. We propose a multi-energy multi-objective scheduling model to optimally manage the supply, demand, and interchange of multiple energy carriers, based on dynamic price and carbon emission signals. Our holistic and integrated approach is applied to a group of 200 smart homes with varying thermal and electric loads, and equipped with different types of smart technologies. The effectiveness of the approach in reducing the home carbon footprint, while remunerating the users, is evaluated using historical and statis tical data of three European countries.

M. NASSEREDDINE , J. RIZK, A. HELLANY, M. NAGRIAL[2016] studied electrical power energy forms an indispensable part of human comfort. Numerous activities would have been impossible without the aid of electricity. The introduction of the PV solar system introduces additional challenges to engineers on how to increase the efficiency of the system. Micro grid PV generations spread world-wide by installing small size PV system on the roof top of residential properties. The maximum output of the PV system is at midday where working families are away from homes. Without the storage system, this energy can only be injected into the electrical grid. This paper introduces the concept of electrical management system for smart home. The proposed smart system allows percentage of the PV generated energy to be used during working hours. Also, the proposed system gives the individual a total control to maximize the use of generated energies, reduce the electricity bills and the impact on the environment.

MARTIN LISKA, MARIAN IVANIC, VLADIMIR VOLCKO, PETER JANIGA[2015] studied that Europe is committed to the 20-20-20 targets to reduce carbon emissions and to secure energy supply. Energy efficiency and renewable energy are seen as key to reach these goals. Both measures all for changes in our energy supply system leading to smart grids for the required innovation. The fundamental architecture of networks build in years ago has been developed in most member states to meet the needs of large, predominantly carbon-based generation technologies. But now the networks will have to integrate decentralized and renewable power generation, also with many small suppliers. More flexible transport of power is needed in response to new energy markets and energy trading, and to the trend towards location of bulk generation far from load. The European Commission has taken a number of actions including a mandate on standardization for smart grids issued in 2011. The final customer with small source has a potential to participate on smart grid features and thus should be involved and motivated throughout several motivation stimulus. One of the key features in the smart grid applications is the demand side service offered to designated parties by smart home automation systems. This paper describes the base of home automation systems upon the smart grid reference architecture. The paper also describes the fundamentals on research of Smart Home Energy Management System and demonstrates the idea of its utilization for demand side management on simulation experiment of low voltage grid with distributed sources.

MEHMET BÜYÜK ,ERCAN AVŞAR &MUSTAFA İNCI[2022] studied the concept of smart homes is considered either to enhance life quality of people or to ensure energy management of buildings, where intelligent technologies are used to achieve the comfort and energy management aims in smart homes. This technology is still under fast development, and it is noticeable that a detailed research study is needed to point out state-of-the-art and future perspectives regarding smart home applications. Thus, considering the developments in smart homes, this paper investigates smart home applications in literature and market, and conducts a systematic overview by considering energy management systems and numerical researches. A comprehensive survey of smart homes is carried out to evaluate their system configurations, functional capabilities, objectives, and hardware applications in this context. Management devices, field devices, tracking systems, small appliances, and communication devices are listed as the five major hardware in the current study. Furthermore, fundamental functions of smart homes are introduced as monitoring, data logging, control, alarm/caution, and management in the current study. Subsequently, state-of-the-art of smart home technology is given to investigate the numeric values of scientific research studies, the percentage values of studies in different discipline areas, the number of scientific studies according to the nations, and the numeric values of smart home appliances. According to the numerical results, it is clear that studies on smart homes/HEMS have increased exponentially after 2000 years. The percentage values of studies in different discipline areas and the number of studies conducted by the leading countries interested in smart homes/HEMS are conducted in this work. The current study also analyzes how the future perspective of smart home technology has been shaped over the years. According to the future perspectives, the numeric values show that the number of smart home applications and their market value are expected to grow in the near future, where smart appliances and market budget are expected to be 75.4 billion units 262.8 billion dollars by 2025, respectively.

MEHIDI HASAN, TOUHIDUL ISLAM TALUKDER, FATEMA TAUZE ZOHORA SAIMA, MD. NAZIM UDDIN JOY, ADRIK DAS, MD. NURSARI HASAN SHEHAM[2022] studied that The paper's object is to develop a smart home automation system with sustainable renewable energy. The paper presents a conceptualization and implementation of developing a smart home system that uses solar panels to maximize the use of abundant renewable energy. This system is created to minimize the carbon footprint and energy consumption. This will simultaneously be a great solution for the climate issues in the world as well while using renewable energy simultaneously. Integrated renewable energy in this project to build an IoT-based smart automated home system. One of the major features of the system is to integrate the sun tracking method for maximum solar power harnessing. In this SHAS or Smart Home Automation System, lighting, climate, entertainment systems, and appliances are all monitored and controlled by the system. Home security systems such as access control, face recognition, and alarm systems are also be included. The project has features like activating loads using a Bluetooth system. The Arduino UNO board, a Bluetooth module controlled by a remote, and an infrared sensor are used to offer a low-cost and user-friendly remote-controlled home automation system in this work. IoT or Internet of Things technology is used to connect device communication in smart home appliances. In this home automation system technologies are used like Wi-Fi, Bluetooth where several types of electrical devices are used for controlling and monitoring various kinds of appliances of a household. This project offers a low-cost, eco-friendly smart home solution for individuals in underdeveloped nations like Bangladesh.

NUR INSAAN MUHAMMAD AKBAR, ZULKIFLI TAHIR, ANDANI[2023] studied that Solar energy becomes more popular for generating electricity in daily lives. Various technologies have utilized solar energy as their power source. One of the technologies that benefit from solar energy is the smart home system. Smart home systems utilize solar panels composed of multiple solar cells arranged in a specific configuration to generate a usable amount of electrical power. This research proposes a fog computing architecture for monitoring solar panel performance in a smart home system. Fog computing, as a distributed computing model, offers several benefits for managing and processing data in the context of the Internet of Things (IoT). We discuss the design and implementation of the proposed architecture and evaluate its effectiveness in terms of system performance and energy efficiency. The results show that proposed fog computing architecture gets better performance in terms of Response Time, CPU Load, and Latency. The results of this study demonstrate the potential of fog computing in improving the performance and reliability of smart home systems, particularly in the context of renewable energy sources such as solar panels

PUJI CATUR SISWIPRAPTINI, ROSIDA NUR AZIZA, RIKI RULI A. SIREGAR, ARIEF RAMADHAN[2024] studied This systematic review synthesizes 93 articles on smart home energy management systems guided by the preferred reporting item for systematic reviews and meta-analysis (PRISMA) framework. Analysis of the sample along with architecture components, communication mechanisms, services provided, and algorithms implemented reveals the proliferation of home automation technologies lacking holistic integration. Setup complexity persists alongside suboptimal efficiency. Structuring research around resident experience rather than technical novelty may forward solutions. Though artificial intelligence holds promise in predictive optimization, deterministic rule-based controls often demonstrate sufficiency. Collaborative initiatives reconciling technical possibilities with user needs can best propel the field.

RIKKE HAGENSBY JENSEN, YOLANDE STRENGERS, JESPER KJELDSKOV, LARISSA NICHOLLS, MIKAEL B. SKOV[2018] studied and has shown that desirable designs shape the use and experiences people have when interacting with technology. Nevertheless, how desirability influences energy consumption is often overlooked, particularly in HCI studies evaluating the sustainability benefits of smart home technology. In this paper, we present a qualitative study with 23 Australian households who reflect on their experiences of living with smart home devices. Drawing on Nelson and Stolterman's concept of desiderata we develop a typology of householders' desires for the smart home and their energy implications. We structure these desires as three smart home personas: the helper, optimiser and hedonist, which align with desiderata's three approaches to desire (reason, ethics and aesthetics). We use these insights to discuss how desirability can be used within HCI for steering design of the smart home towards sustainability.

THOMAS GEORGE, A. IMMANUEL SELVAKUMAR[2024] studied A smart home energy management system plays an important role in improving the efficiency of an energy distribution system and also helps to reduce the carbon footprint of the power utility company. For a developing country like India, one of the main challenges faced while integrating an energy management system and renewable energy technology is the migration cost faced by the user from the existing system. The existing energy policy of the nation or the com munity should be reformed in such a way that the user who is willing to adapt to an energy management system should be properly rewarded. Smart appliances and IoT-enabled devices reduce wiring complexity in any conventional home and the smart metering facility aids in the bidirectional communication between consumers and utility companies. But how does it take care of user privacy? What are the reasons behind the user's negligence on-demand response schemes in India? Through a case study, it was observed that the power consumption of domestic consumers in India increased over the years. It was also observed through an energy survey of 200 low-tension domestic consumers that a simple reengineering of lighting loads can save up to 4.68 Megawatt-hour of energy in a year. The paper also identified the negative impact of the inclining block rate billing scheme by comparing the bimonthly energy consumption pattern of consumers and also proposed a new billing scheme. The paper also reviews the types of optimization methods available for load scheduling. This paper is an attempt to enlighten readers on the importance of adopting a sustainable home energy management system, as a socio-economic commitment towards a green future.

YUNLONG MA, XIAO CHEN, LIMING WANGL, JIANLAN YANG[2021] studied Electricity market reform provides the conditions for demand-side load resources to be incorporated into the supply–demand regulation, and the increase of residential-side electrification level makes residential load resources a high-quality resource for demand response (DR). Resident home appliances participate in the "two-way interaction" of the powergridintheformofDR,whichcaneffectivelyalleviate the tensionof power supplyand consume clean energy, to improve the safe and stable operation of the power system. Firstly, this article summarizes the structure and functions of the home energy management system (HEMS). Secondly, it discusses the key technologies of the HEMS, starting from an advanced metering infrastructure (AMI) and DR technology. Finally, it analyzes the control strategies of the HEMS, including component models and various optimal scheduling algorithms, and describes the challenges of the HEMS.

YASSER AL SULTAN, BEN SALMA SAMI, BASSAM A. ZAFAR[2021] studied home energy management system has been selected as an attractive research issue due to its ability to enhance energy security by including devices, entertainment systems, security systems, environmental controls, etc. Home automation is incorporated as a potential technology to ensure efficient electricity performance without interruption, solve power demand problems and coordinate devices with innovative technologies. In this context, our proposal seeks to implement an accurate home energy management system. The proposed approach aims to improve uninterrupted electricity production and provide comfortable services to families. To implement correct system operations and meet each device's power demand, a Reel Time Energy Management System (RT-EMS) will be implemented and discussed through some required tasks using the Multi-Agent System (MAS). Each agent will be determined according to some criteria to implement the appropriate design and meet each device's power demand. The obtained results will show that the proposed system meets the general objectives of RT-EMS.

2.2 EXISTING SYSTEMS

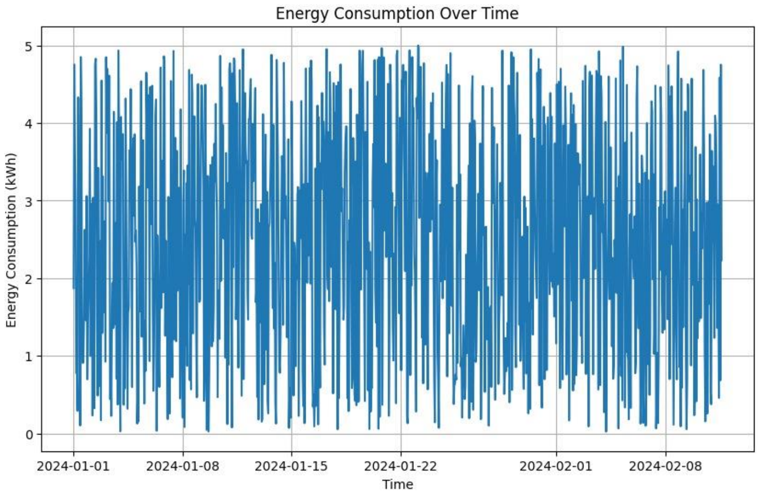


Fig 2.1 Energy Consumption Over Time

In Fig 2.1, the graph shows energy consumption (in kWh) over time from January 1st to February 8th, 2024, with significant fluctuations in daily usage. Peaks represent periods of high energy demand, likely corresponding to increased household or appliance activity, while troughs indicate lower usage, possibly during off-peak hours like nighttime. The overall pattern suggests some cyclical behavior, possibly reflecting daily or weekly routines. Analyzing such data helps identify periods of high consumption, which can be targeted for optimizing energy efficiency and reducing costs.

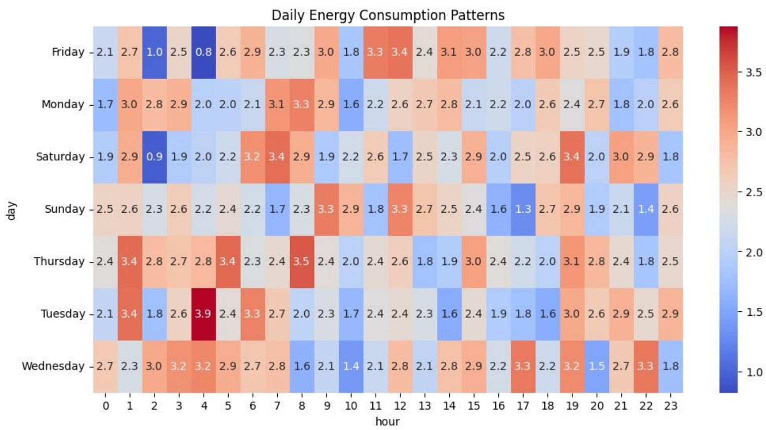


Fig 2.2 Daily Energy Consumption Patterns

In Fig 2.2, this heatmap displays the daily energy consumption patterns across different days of the week (Friday to Wednesday) and hours of the day (0 to 23). The color intensity represents the energy consumption, with red indicating higher values and blue showing lower values. Each cell reflects the energy usage for a specific day and hour, with the scale on the right representing the consumption range from -1.0 to 3.9. Notably, energy consumption peaks around early mornings (hours 4 to 6) on Tuesdays and Thursday, as indicated by deep red colors. In contrast, some late-night periods (e.g., Friday 1 a.m. and Saturday 3 a.m.) show lower consumption with blue tones. This pattern provides insight into fluctuating energy usage trends across different days and times.

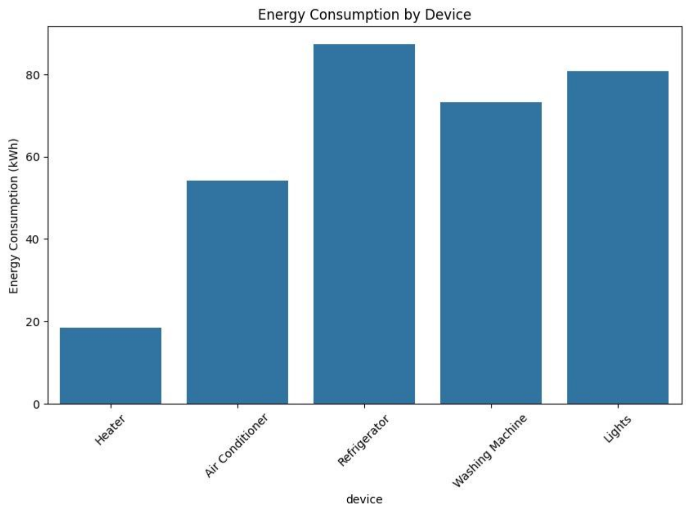


Fig 2.3 Energy Consumption by Device

In Fig 2.3, the bar chart shows the energy consumption of various household devices in kilowatt-hours (kWh). The refrigerator consumes the most energy, nearing 90 kWh, followed closely by lights and the washing machine, each consuming about 80 kWh. The air conditioner also has a significant consumption level, at around 60 kWh. In contrast, the heater consumes the least energy, around 20 kWh. This chart highlights that the refrigerator and lighting systems are the biggest energy consumers in this dataset, whilethe heater uses much less energy.

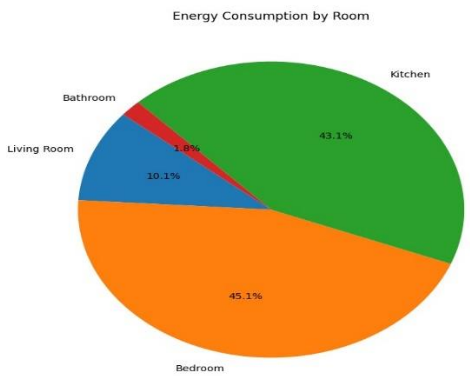


Fig 2.4 Energy Consumption by Room

In Fig 2.4, this pie chart represents the energy consumption distribution by room. The bedroom accounts for the largest share, using 45.1% of the total energy, followed closely by the kitchen at 43.1%. The living room consumes 10.1%, while the bathroom uses the least energy at 1.8%. This suggests that most energy consumption occurs in the bedroom and kitchen, potentially due to appliances and devices commonly used in these areas, while the bathroom has a minimal energy footprint.

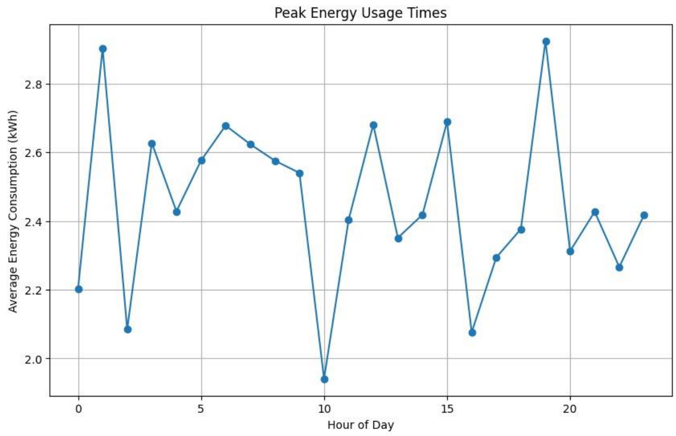


Fig 2.5 Peak Energy Usage Times

In Fig 2.5, The energy consumption throughout the day shows noticeable fluctuations, with significant peaks occurring around midnight (Hour 0) and between 20:00 to 21:00, where the average consumption exceeds 2.8 kWh. On the other hand, there is a sharp dip in energy usage around 10:00, reaching as low as 2.0 kWh. This pattern suggests higher energy demands during late-night and evening hours, likely driven by residential or commercial activities, while the mid-morning dip could be attributed to reduced operational requirements during that time

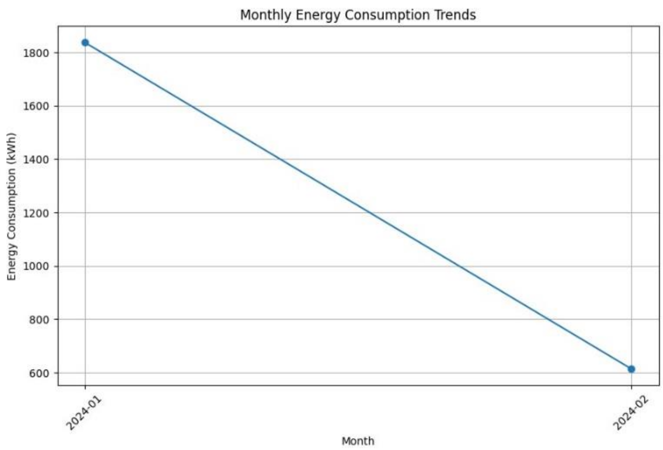


Fig 2.6 Monthly Energy Consumption Trend

In Fig 2.6, there is a steep decline in energy consumption from January to February, with usage dropping from approximately 1800 kWh in January to around 600 kWh in February. This suggests a substantial reduction in energy demand, which could be due to a variety of factors such as seasonal changes, energy efficiency measures, or variations in operational activities. The marked decrease may indicate effective energy-saving strategies or shifts in energy usage patterns during the two months.

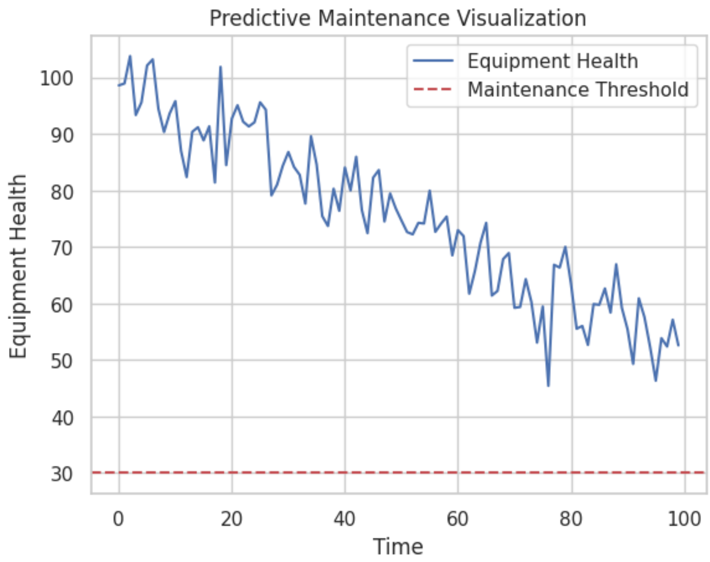


Fig 2.7 Predictive Maintenance Visualization

In Fig 2.7, The graph illustrates the decline in equipment health over time, indicating a trend towards degradation. The equipment health starts above 100 but consistently decreases, showing increased variability and abrupt drops as time progresses. A maintenance threshold is set at 30, and as the equipment health approaches this threshold, it suggests that without intervention, the equipment could soon fall below this critical level, indicating a need for maintenance. This visualization is useful for predictive maintenance, helping identify the optimal time to perform maintenance to prevent equipment failure.

2.2.1 DRAWBACKS:

Existing systems for smart home energy insights face several key drawbacks. High initial costs for hardware such as sensors, smart meters, and connected appliances can be a barrier for many homeowners. These systems often generate overwhelming amounts of data, making it difficult for users to interpret and act on energy-saving opportunities. Interoperability issues between different devices and platforms further complicate system integration, while the dependence on constant internet connectivity makes them vulnerable to outages and disruptions. Privacy and security concerns arise from the detailed energy usage data collected, which can also expose systems to cyber threats. Additionally, many systems provide limited actionable recommendations, leaving users unsure of how to optimize energy consumption effectively. Accuracy challenges, especially in systems like Non-Intrusive Load Monitoring (NILM), can lead to incorrect insights, while ongoing maintenance and lack of long-term support for older devices further reduce their effectiveness. These challenges highlight the need for more affordable, user-friendly, and secure solutions in the smart home energy market.

Existing systems for smart home energy insights face both practical and technical drawbacks. The high initial costs for hardware such as sensors, smart meters, and connected devices can deter widespread adoption. These systems often generate large amounts of data that can overwhelm users, especially when the insights are not presented in actionable formats. From a technical standpoint, interoperability issues between different smart devices and platforms hinder seamless integration, as many devices use proprietary protocols, making it difficult to create a unified system. Internet dependence is another issue, as system functionality can be disrupted by outages, affecting real-time monitoring and control.

Security vulnerabilities are a significant technical concern, as the connected nature of these systems exposes them to potential cyber-attacks, data breaches, or unauthorized control of appliances. Accuracy is another technical challenge, especially with Non-Intrusive Load Monitoring (NILM) systems, which struggle to distinguish between appliances with similar power consumption profiles, leading to less reliable energy insights. Furthermore, many systems provide limited analytics and lack the ability to deliver deep insights or predictive maintenance recommendations, hindering their effectiveness in long-term energy management. Additionally, smart devices and appliances can quickly become obsolete due to rapid technological advances and lack of ongoing software support, posing long-term sustainability issues. Finally, technical challenges such as scalability and high computational demands for processing real-time data across multiple devices can limit the efficiency and performance of smart energy systems in larger homes or complex setups.

2.3 PROPOSED SYSTEM:

The proposed Smart Home Energy Management System (SHEMS) is a comprehensive solution designed to optimize energy consumption in modern households, integrating renewable energy sources like solar power and providing real-time insights to homeowners. The system is built around several core modules that work together to enhance energy efficiency, reduce costs, and promote sustainability by enabling intelligent decision-making based on predictive analytics and real-time data.

1. Energy Monitoring and Data Collection Module

At the heart of the system is the Energy Monitoring and Data Collection Module, which uses IoT-based smart meters to monitor real-time energy consumption at the appliance level. Each appliance’s energy usage is tracked in detail, enabling granular visibility into household power consumption. In addition, external factors like weather conditions, including temperature, humidity, and solar radiation, are integrated into the dataset. By including data from solar panels and other renewable sources, the system accounts for energy generation and storage, making it a holistic energy management platform. The gathered data is stored in cloud databases such as AWS or Azure, ensuring scalability, security, and easy access for future analysis. The cloud infrastructure allows for real-time data streaming, historical trend analysis, and the ability to scale as more devices and sensors are integrated into the system.

2. Data Preprocessing and Cleaning Module

Before the collected data can be used for further analysis, it undergoes preprocessing to ensure high quality and consistency. The Data Preprocessing and Cleaning Module is responsible for handling missing data, outlier detection, and ensuring that all data is normalized for effective comparison. Tools like Python's pandas library and SQL are utilized for merging energy usage data with weather data, ensuring that patterns between appliance use and external factors are captured accurately. This module also extracts key features that are most relevant for energy consumption prediction, such as peak solar generation hours, seasonal weather patterns, and appliance-specific behaviors. This step is crucial in preparing the data for machine learning models, ensuring high accuracy in the predictions and optimization decisions that follow.

3. Predictive Modeling Module

One of the standout features of SHEMS is its ability to predict future energy consumption, allowing homeowners to proactively manage their energy usage. The Predictive Modeling Module uses machine learning algorithms like Linear Regression, Random Forest, and Neural Networks to forecast energy demand based on past usage patterns, weather conditions, and appliance behavior. By incorporating weather data (e.g., expected temperature or solar radiation) alongside household consumption patterns, the system can provide more accurate predictions for upcoming days or weeks. These predictions enable homeowners to adjust their behavior, such as running energy-intensive appliances during non-peak hours, when energy costs might be lower. Additionally, the system provides real-time predictions, empowering users to make on-the-fly decisions that optimize their energy usage, minimize wastage, and avoid high-energy periods where electricity might be more expensive.

4. Renewable Energy Optimization Module

SHEMS goes beyond monitoring by actively optimizing the use of renewable energy, particularly solar power. The Renewable Energy Optimization Module tracks energy generation from solar panels and the state of charge of home battery systems. Using smart scheduling algorithms, it determines the best times to run high-energy appliances, such as dishwashers or washing machines, during periods of peak solar generation. This module also manages grid interactions, allowing homeowners to sell excess solar energy back to the grid during times of surplus. By leveraging dynamic pricing and grid conditions, the system can maximize the financial benefits of selling energy while ensuring the household has enough stored power for its needs. The optimization logic balances real-time energy needs, solar generation forecasts, and storage levels, creating a smooth and efficient energy management cycle that reduces reliance on the grid and increases household autonomy.

5. User Interface and Reporting Module

The system is equipped with a highly intuitive User Interface and Reporting Module, giving homeowners full visibility into their energy consumption and production. Built using web frameworks like React and visualization tools like Plotly, the dashboard offers real-time insights into how much energy each appliance is consuming, how much energy is being generated from solar panels, and how much is being saved or sold back to the grid. Homeowners can access this data from both web and mobile platforms, ensuring they stay informed and in control, no matter where they are. The dashboard includes features like predictive trends, showing anticipated energy consumption and cost over the next few days, and cost-saving recommendations that suggest optimal times to run appliances. Additionally, the system generates alerts and notifications, informing users of high energy consumption periods, potential maintenance needs, or opportunities to optimize energy use based on real-time solar generation or grid pricing.

Conclusion:

The Smart Home Energy Management System offers an integrated solution for modern households looking to improve energy efficiency, reduce costs, and embrace renewable energy. Through the combination of real-time monitoring, predictive modeling, and renewable energy optimization, homeowners can make data-driven decisions that align with their consumption patterns and sustainability goals. With its ability to manage solar energy generation, forecast future energy use, and seamlessly interact with the grid, SHEMS empowers users to reduce their reliance on traditional energy sources, optimize appliance efficiency, and ultimately, contribute to a greener, more sustainable future.

2.3.1 FEATURES:

The Smart Home Energy Management System is designed to provide homeowners with a robust and highly efficient solution for managing energy consumption, reducing costs, and maximizing sustainability. The system begins with real-time monitoring of energy usage across all household appliances, using IoT-enabled smart meters that continuously track and display appliance-specific energy data on an intuitive user dashboard. This granular level of monitoring allows users to easily identify high-energy-consuming appliances such as air conditioners, refrigerators, and washing machines, enabling more informed decisions to optimize their usage. Additionally, the system integrates external data sources, such as weather conditions (temperature, humidity, wind speed) and solar power generation, to provide a holistic view of how environmental factors affect energy consumption patterns. By correlating this external data with appliance-level consumption, the system can further optimize energy usage based on real-time weather conditions.

The inclusion of predictive modeling, powered by machine learning algorithms like Linear Regression and Random Forest, allows the system to forecast future energy consumption based on historical usage, weather patterns, and appliance behavior. This feature provides insights into potential peak consumption periods and suggests energy-saving strategies, such as shifting high-energy tasks to off-peak hours or adjusting settings to reduce unnecessary consumption. The system also includes a renewable energy optimization module that efficiently integrates solar energy into household consumption. This module tracks solar generation in real-time, manages battery storage, and allows for the selling of excess energy back to the grid. By doing so, homeowners can reduce their dependence on grid power, lower their electricity bills, and even earn credits for surplus energy generation.

Further enhancing efficiency, the system incorporates smart scheduling algorithms that automatically run energy-intensive appliances like dishwashers and washing machines during off-peak hours or when solar energy is most abundant. This intelligent scheduling reduces energy costs while ensuring that appliances operate when renewable energy sources are available. A user-friendly dashboard provides real-time visualizations of energy consumption, solar generation, and appliance usage through interactive charts and graphs, offering clear insights and predictive recommendations for energy optimization. In addition to monitoring, the system sends predictive maintenance alerts when it detects inefficiencies or anomalies in appliance performance, helping prevent costly repairs and extending the lifespan of appliances.

For added convenience, the system generates detailed, automated energy usage reports that provide users with a comprehensive analysis of their consumption patterns, highlighting key trends, peak usage times, and cost-saving opportunities. The smart grid integration feature allows homes with solar panels to sell excess energy back to the grid, offsetting electricity costs and contributing to grid stability during peak demand times. Automated energy usage alerts notify users when consumption exceeds a pre-set threshold or when there's an opportunity to shift tasks to save energy, allowing for proactive management. The system also employs occupancy-based energy adjustments, automatically regulating heating, cooling, and lighting based on whether rooms are occupied or vacant, thereby saving energy without sacrificing comfort.

In summary, the Smart Home Energy Management System delivers a powerful combination of real-time monitoring, predictive analytics, renewable energy integration, and smart automation to provide homeowners with an energy-efficient, cost-effective, and environmentally friendly solution. By leveraging advanced technology, the system empowers users to reduce their electricity bills, make better use of renewable energy, prevent appliance overconsumption, and maintain a sustainable lifestyle with minimal effort.

3. DATASET DESCRIPTION:

Data description, also referred to as data summarization or profiling, is an essential step in data analysis. It involves providing a concise overview of a dataset's key characteristics, structure, and distribution. This process helps create a clear understanding of the dataset's content and serves as a foundational exploration before more advanced analyses, allowing analysts and researchers to gain valuable initial insights into the data they're working with.

3.1 Data collection

Data collection is the systematic process of gathering, capturing, and accumulating information or observations from various sources to create a dataset for analysis. It is a fundamental step in the research, analysis, and decision-making processes across various fields, including academia, business, healthcare, and social sciences. Proper data collection ensures that accurate, relevant, and reliable information is available for analysis and interpretation**.**

https://www.kaggle.com/datasets/taranvee/smart-home-dataset-with-weather-information/data

This CSV file contains the readings with a time span of 1 minute OF 350 DAYS of house appliances in kW from a smart meter and weather conditions of that region. The dataset "Smart Home Energy Usage" provides a unique opportunity to analyze and understand energy consumption patterns in smart homes. With sustainability and energy efficiency being key goals in modern living, this dataset enables insights into how different appliances contribute to overall energy usage. By exploring the dataset, we can identify trends in energy consumption, correlations between household activities, and environmental factors such as temperature and humidity. These findings can be instrumental in developing strategies for reducing energy costs, optimizing appliance usage, and contributing to greener living environments. The Smart Home Energy Consumption dataset is a detailed compilation of energy usage data collected from a residential environment, focusing on both overall household energy consumption and appliancespecific usage. The dataset is enriched with weatherrelated variables, allowing for a comprehensive analysis of how external environmental factors influence energy demand. Below is a description of the key components of the dataset:

1. Energy Consumption Variables

- House overall [kW]: The total energy consumption of the entire house, measured in kilowatts (kW). This is the primary variable for assessing the overall energy demand in the home.
- Dishwasher [kW]: The energy consumption specifically attributed to the dishwasher, in kilowatts.
- Furnace 1 [kW]: The energy usage of the first furnace in the house, measured in kilowatts.

- Furnace 2 [kW]: The energy consumption of the second furnace, if present, in kilowatts.
- Home office [kW]: The energy used by appliances and equipment in the home office, in kilowatts.
- Fridge [kW]: The energy consumption of the refrigerator, in kilowatts.

2. Weather Variables

- temperature: The ambient temperature at the time of data collection, recorded in degrees Celsius. Temperature can significantly impact energy usage, particularly for heating and cooling systems.
- humidity: The relative humidity percentage, which can influence how often and intensely heating, ventilation, and air conditioning (HVAC) systems are used.
- visibility: This metric indicates the visibility in miles at the time of data recording. While it may seem less directly related, it can correlate with other weather conditions that affect energy consumption.
- pressure: Atmospheric pressure, measured in hectopascals (hPa), which can be linked to weather patterns influencing energy use.
- windSpeed: The speed of the wind, measured in meters per second (m/s). Wind speed might impact the operation of heating systems, especially in areas prone to drafts or where outdoor air intake systems are used.
- cloudCover: The percentage of the sky covered by clouds, which can affect the amount of natural light available and subsequently the use of artificial lighting.
- dewPoint: The temperature at which air becomes saturated with moisture and dew forms, measured in degrees Celsius. This variable is related to humidity and can affect the perception of temperature indoors, influencing heating and cooling needs.

3. Derived Variables

- Hour: A derived variable representing the hour of the day extracted from the time column. It is used to analyze energy consumption patterns at different times of the day, helping to identify peak usage periods.

Summary

- This dataset provides a rich, multidimensional view of energy consumption in a smart home, enabling the exploration of correlations between appliance usage, overall energy demand, and environmental factors. It is particularly suited for timeseries analysis, predictive modeling, and the development of strategies to optimize energy efficiency within residential settings.

SUMMARY STATISTICS:

Name	Mean	Median	Standard Deviation	Minimum	Maximum
Total energy consumption (kWh)	0.874387	0.728775	0.663169	0.00	11.673700
Dishwasher [kW]	0.034093	0.000033	0.198778	0.00	1.393650
Furnace 1 [kW]	0.166443	0.064350	0.201002	0.000017	1.934083
Furnace 2 [kW]	0.192499	0.087650	0.218613	0.000367	0.791033
Home office [kW]	0.078458	0.041900	0.096479	0.000383	0.971750
Fridge [kW]	0.054785	0.005333	0.071650	0.000133	0.851267
Wine cellar [kW]	0.025871	0.007133	0.046112	0.000100	1.189667
Garage door [kW]	0.013898	0.012883	0.010968	0.000233	1.060433
Kitchen 12 [kW]	0.001710	0.000650	0.019963	0.00	0.916450
Barn [kW]	0.059656	0.031867	0.156444	0.00	7.027900
Microwave [kW]	0.009979	0.004033	0.089256	0.00	1.892417
Living room [kW]	0.037075	0.001567	0.098913	0.00	0.392617
Solar [kW]	0.074542	0.003450	0.135100	0.00	0.613883
temperature	36.892142	36.900000	13.990549	-12.640000	77.720000
humidity	0.598518	0.600000	0.187243	0.130000	0.960000
visibility	9.307774	10.000000	1.639072	0.830000	10.000000
apparentTemperature	32.094232	32.090000	16.935898	-32.080000	77.720000
pressure	1015.924197	1016.140000	8.993801	986.400000	1036.620000
windSpeed	7.581206	6.930000	4.232902	0.090000	22.910000
windBearing	204.415348	212.000000	109.021957	0.00	359.000000
dewPoint	22.887060	23.370000	13.957162	-27.240000	58.370000
Predicted House Overall [kW]	0.948929	0.787725	0.634382	0.035300	11.674433

The data shows that average energy use is 0.874 kW, with a max of 11.674 kW and a median of 0.729 kW, indicating moderate but variable usage. Energy generation is low, averaging 0.075 kW. Environmental factors like temperature (mean 36.89°C) and humidity (mean 0.60) show normal variation, influencing energy consumption patterns.

3.2 Database Design

3.3 Description of Modules

1. Energy Usage Data:

- This refers to the raw data collected from different energy-consuming devices in a home, like HVAC, lights, and appliances.

2. Collected by Smart Meters:

- Smart meters gather real-time data on energy usage from home devices, serving as the input point for the energy management system.

3. Data Preprocessing:

- This module processes the raw data from smart meters, cleaning and organizing it for further analysis.

4. Device and Sensor Data:

- This captures detailed data from specific home devices and sensors like HVAC systems, lights, and other appliances.

5. Smart Home Devices:

- This refers to smart appliances and systems within the home that can be controlled and monitored through a central platform.

6. HVAC, Lights, Appliances:

- These are specific categories of devices that consume energy in the home and are monitored for usage patterns.

7. Control Signals:

- Signals sent to smart home devices to adjust their operation (e.g., turn off, adjust power settings) based on data insights.

8. User Interface:

- The user interacts with the system through an interface that displays energy data, controls, and insights.

9. Display:

- The user interface outputs energy usage patterns and recommendations to help users manage energy consumption.

10. Data Storage - Cloud:

- The preprocessed data is stored in a cloud system, enabling remote access and large-scale storage for analysis.

11. Data Analytics:

- This module analyzes stored data to extract insights, detect patterns, and identify anomalies in energy usage.

12. Usage Trends:

- Analytics uncover trends in energy consumption over time, helping users understand usage patterns.

13. Insights: Usage Patterns:

- Based on trends, the system provides insights on regular consumption behavior, enabling better energy management.

14. Anomaly Detection:

- This identifies unusual or unexpected energy consumption patterns, signaling potential inefficiencies or faults in devices.

15. Insights: Unusual Consumption:

- Provides alerts and insights into abnormal energy usage, helping users identify issues such as device malfunctions or inefficiencies.

16. Energy Optimization:

- Focuses on improving energy efficiency by optimizing device usage and providing recommendations to lower energy consumption.

17. Insights: Suggested Actions:

- The system suggests actions users can take to optimize energy usage, such as scheduling device operation times or adjusting settings.

18. Energy Dashboard:

- A centralized platform where all insights, trends, control options, and optimization suggestions are displayed to the user. It helps users monitor, manage, and optimize their energy consumption in real-time.

4. DATA ANALYSIS:

Data analysis involves inspecting, cleaning, transforming, and interpreting data to uncover insights, patterns, and trends. By applying various techniques and tools, it extracts meaningful information from raw data, facilitating informed decision-making and problem-solving. Widely used across fields like business, healthcare, and education, data analysis empowers organizations to make evidence-based conclusions and optimize processes. It includes tasks such as data visualization, statistical analysis, and machine learning to reveal hidden knowledge within datasets, ultimately driving strategic, informed actions.

4.1 ANALYSIS AND INFERENCE

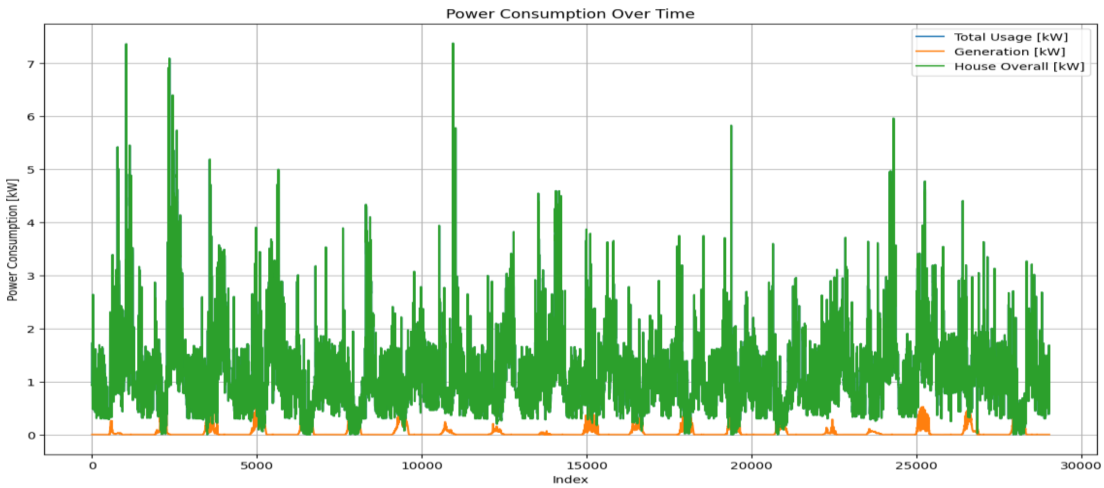


Fig 4.1 Power Consumption Over Time

The data visualization illustrates power consumption over time across various categories. The X-axis represents the row index, serving as a proxy for time since no explicit timestamps are provided, while the Y-axis shows power consumption in kilowatts (kW). Three lines are plotted: the blue line (Total Usage [kW]) represents cumulative power usage, the orange line (Generation [kW]) shows power generation over time, and the green line (House Overall [kW]) reflects overall household power consumption, which includes various appliances and systems. Notably, the green line fluctuates significantly, likely due to high-power appliances being activated, and mirrors the blue line, indicating that other consumption sources might not be accounted for. The orange line, consistently lower than the others, suggests steady power generation but less than consumption.

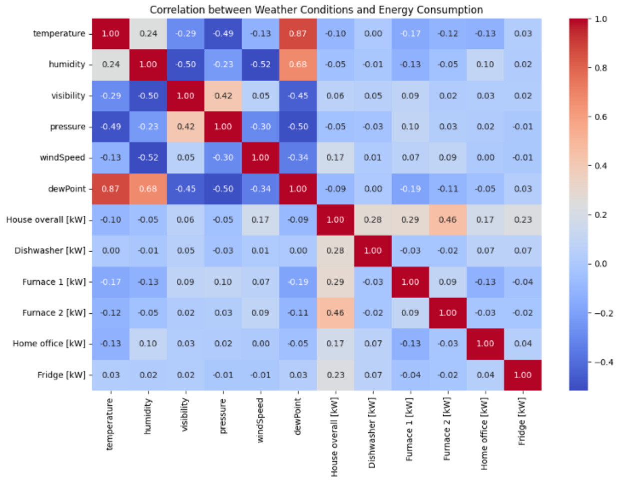


Fig 4.2 Correlation between Weather Conditions and Energy Consumptions

This heatmap shows correlations between weather conditions and energy consumption, with values from -1 (negative) to 1 (positive). Red represents positive correlations, blue represents negative, and color intensity reflects the correlation strength.Key findings: a strong positive correlation (0.87) between temperature and dew point, and a moderate negative correlation (-0.49) between temperature and pressure. Household energy usage correlates positively with appliances like the dishwasher (0.28), furnace (0.46), and fridge (0.23). Dew point is positively linked to humidity (0.68), while wind speed shows a moderate negative correlation with pressure (-0.30). These patterns suggest weather data could help optimize energy use and appliance efficiency

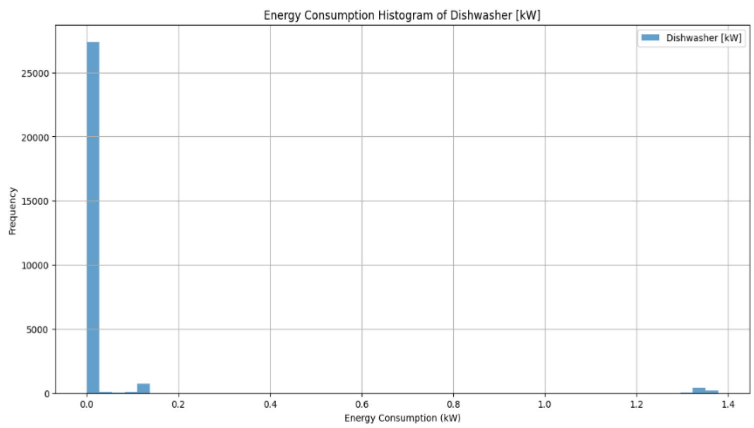


Fig 4.3 Energy Consumption Histogram of Dishwasher [kW]

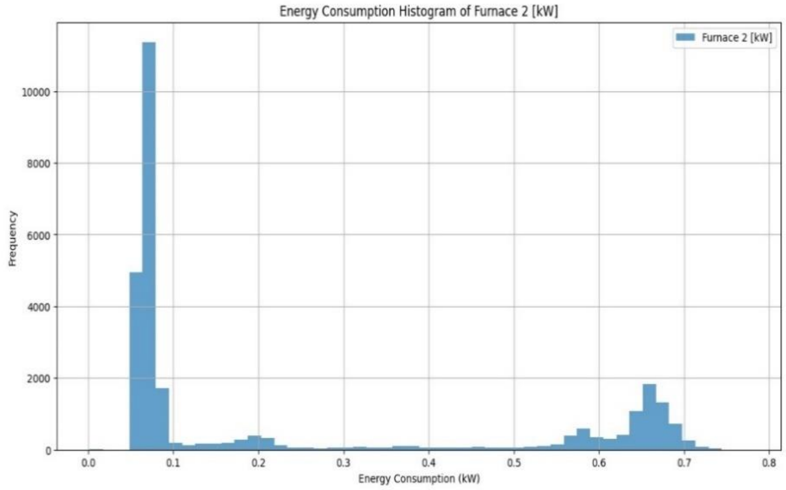


Fig 4.4 Energy Consumption Histogram of Furnace 2 [kW]

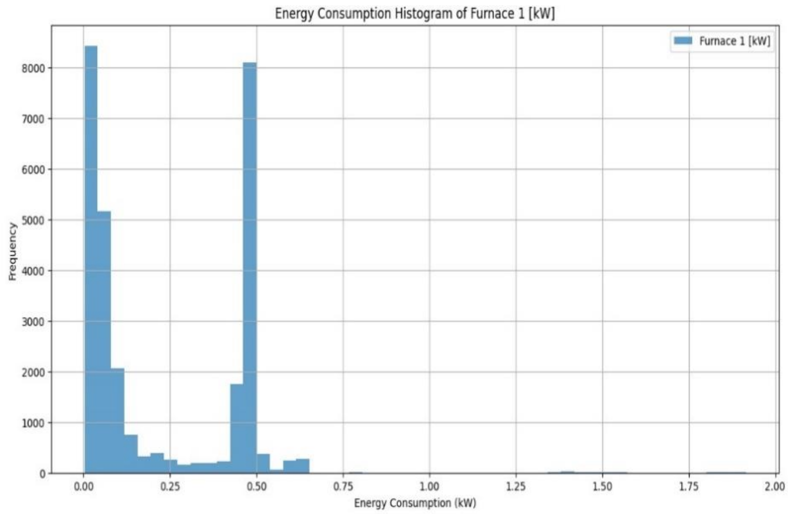


Fig 4.5 Energy Consumption Histogram of Furnace 1 [kW]

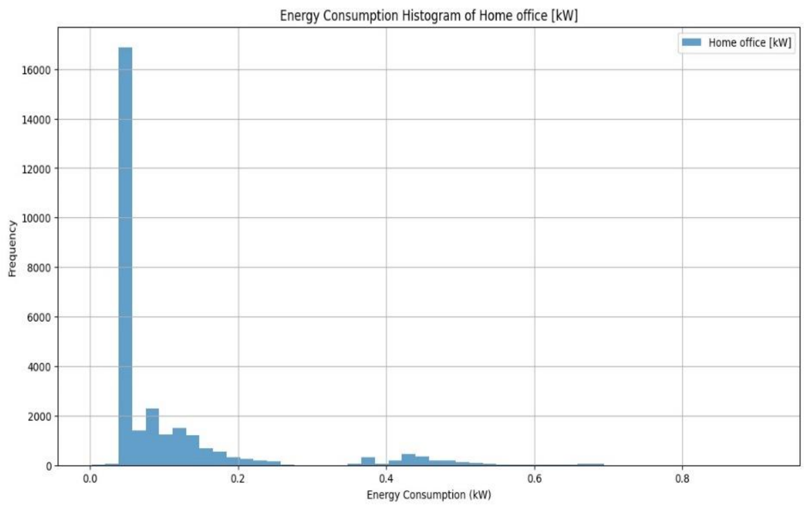


Fig 4.6 Energy Consumption Histogram of Home office [kW]

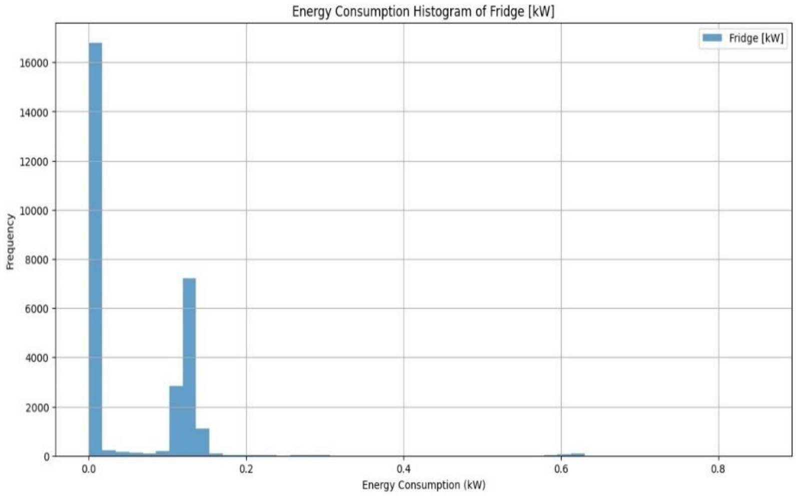


Fig 4.7 Energy Consumption Histogram of Frtidge [kW]

The histograms of energy consumption for appliances such as Furnace 1, Dishwasher, Home Office, and Fridge illustrate distinct patterns. Furnace 1 shows two dominant peaks at 0 kW and 0.5 kW, indicating frequent state changes between these values. The Dishwasher's energy consumption is mostly clustered around 0 kW with a smaller peak near 1.4 kW, likely during specific cycles. The Home Office operates mostly at low power, with a steady decline in energy use up to 0.3 kW, while the Fridge shows consistent low consumption around 0.1 kW. Two regression models, Linear Regression and Random Forest Regressor, were used to analyze energy consumption. Linear Regression, a simpler, interpretable model, helps in understanding the linear relationships between features and energy consumption (e.g., temperature negatively impacts consumption with a coefficient of -0.096). The model has an intercept of 6.744, an MAE of 0.487, and an MSE of 0.438. On the other hand, Random Forest, an ensemble method that handles non-linear relationships, provides better accuracy with an MAE of 0.358 and an MSE of 0.245, highlighting its robustness in complex datasets. Feature importance analysis in Random Forest shows pressure as a key predictor of energy use. Additionally, a Neural Network model was trained, producing an MAE of 0.551 and an MSE of 0.492, but it is less accurate than Random Forest. Linear Regression is useful for understanding feature relationships, while Random Forest offers better predictive performance for complex data.

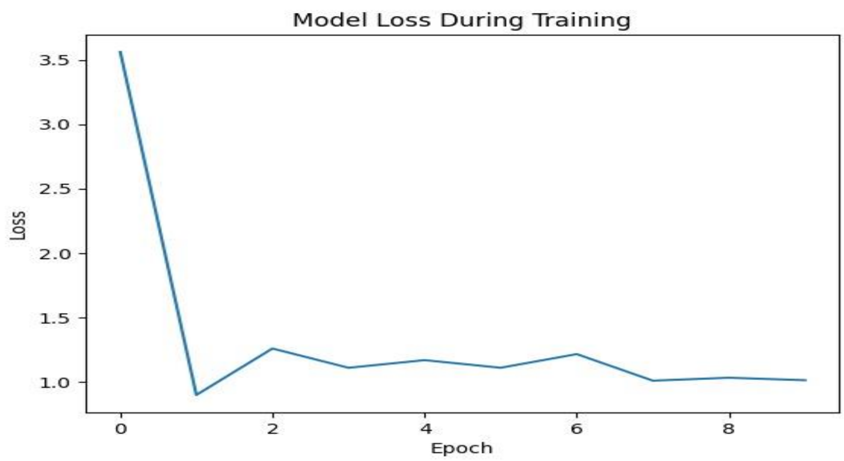


Fig 4.8 model loss during training

The neural network model for energy consumption prediction consists of several layers. The input layer is a dense layer with 64 neurons and the ReLU activation function, defined by the input shape, which corresponds to the number of features in the training data. This is followed by a hidden layer, also with 64 neurons and ReLU activation, and finally, an output layer with one neuron to predict a continuous value. The ReLU activation function introduces non-linearity, allowing the model to learn complex patterns. The model is compiled using the Adam optimizer and the mean squared error (MSE) as the loss function, which is suitable for regression tasks. During training, the model is fitted to the data for 10 epochs with a batch size of 32, and the training progress is displayed. After training, predictions are made on the test set, and model performance is evaluated using metrics such as mean absolute error (MAE) and MSE, with lower values indicating better performance. Neural networks are ideal for capturing non-linear relationships, offering flexibility and automatic feature learning, making them well-suited for complex datasets.

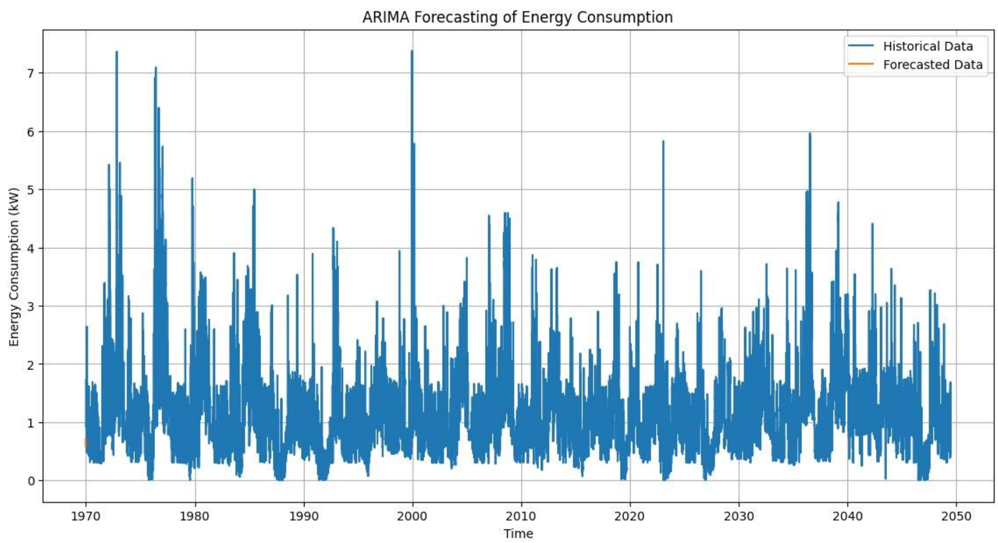


Fig 4.9 Arima Forecasting of Energy Consumption

In addition, an ARIMA (5,1,0) model was employed for time-series analysis, with results indicating key parameters such as a Log Likelihood of -6711.799, an AIC of 13435.597, and a BIC of 13485.254. Significant autoregressive coefficients were found, with all p-values below 0.05. The Ljung-Box test yielded a p-value of 0.38, indicating no significant autocorrelation in residuals. However, the Jarque-Bera test for normality showed a high value of 2121114.45, suggesting non-normal residuals. The heteroskedasticity test indicated a variance of 0.62, with the data skewed by 0.57 and a kurtosis of 44.86, reflecting heavy-tailed data.

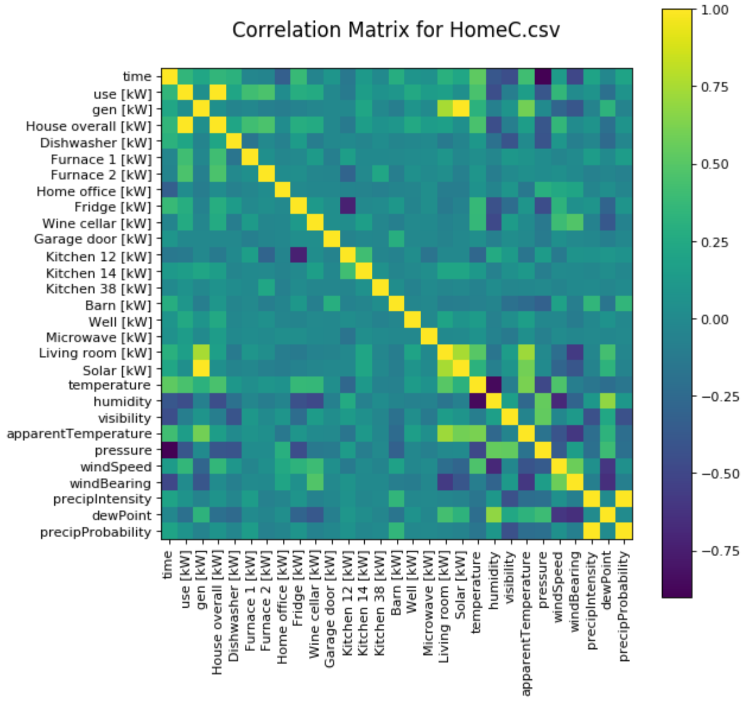


Fig 4.10 Correlation Matrix

Correlation Matrix: This heatmap shows the correlation coefficients between various appliances and environmental variables from the dataset "HomeC.csv." High positive correlations (yellow) indicate a direct relationship between two variables, such as appliances using similar power during certain periods or environmental factors affecting their usage. Darker shades (purple/blue) indicate negative or low correlations. Notably, some variables (like temperature, humidity) have strong correlations with energy usage in specific appliances, indicating environmental influence on power consumption.

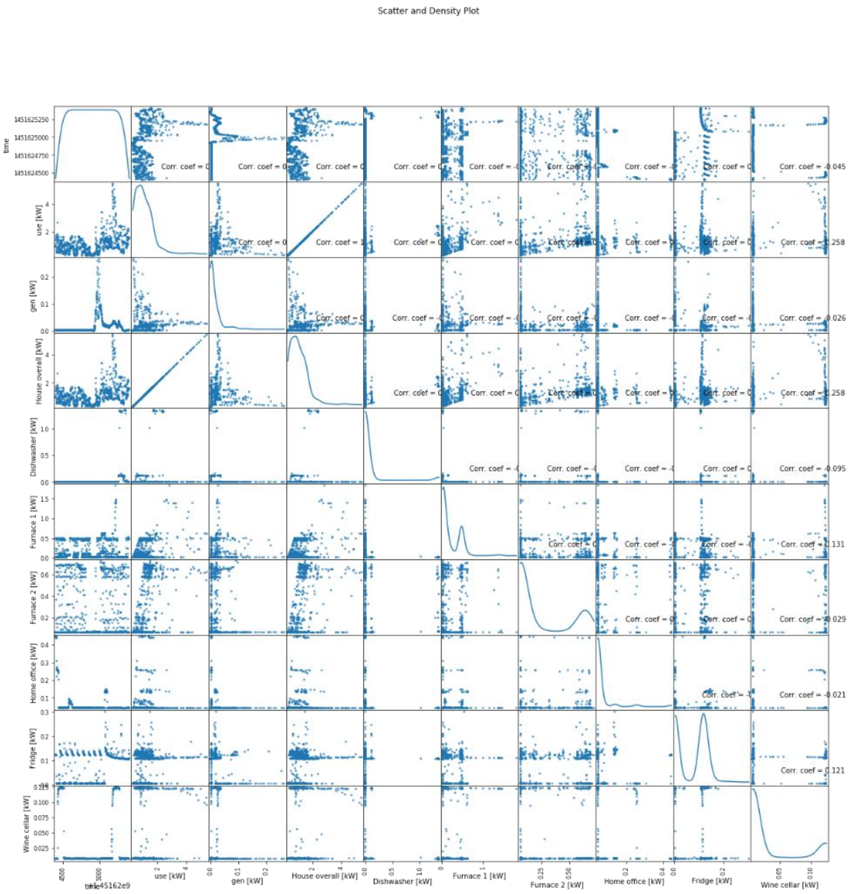


Fig 4.11 Pairplot

This pair plot matrix provides a comprehensive view of the relationships between variables in a dataset. The scatter plots in the lower triangle depict the pairwise interactions, with tightly clustered points suggesting stronger relationships and more dispersed points indicating weaker or no correlation. The upper triangle presents the correlation coefficients for each variable pair, giving a numerical sense of the strength and direction of the relationship—positive values reflect direct correlations, while negative values indicate inverse relationships.

The diagonal contains the distribution plots (such as histograms or kernel density estimates), showing how each variable is distributed individually, allowing us to spot skewness, multi-modal distributions, or potential outliers. For instance, variables with a normal distribution would show smooth, bell-shaped curves, while skewed or multi-peaked distributions would appear irregular.

The scatter plots also help identify non-linear relationships or clusters within the data, potentially hinting at more complex interactions not captured by the linear correlation coefficients. The presence of outliers or unusual patterns in the plots could signal data anomalies or the need for deeper analysis. Overall, this matrix is a useful tool for quickly assessing correlations, distributions, and patterns across multiple variables, offering a visual and numerical foundation for further analysis.

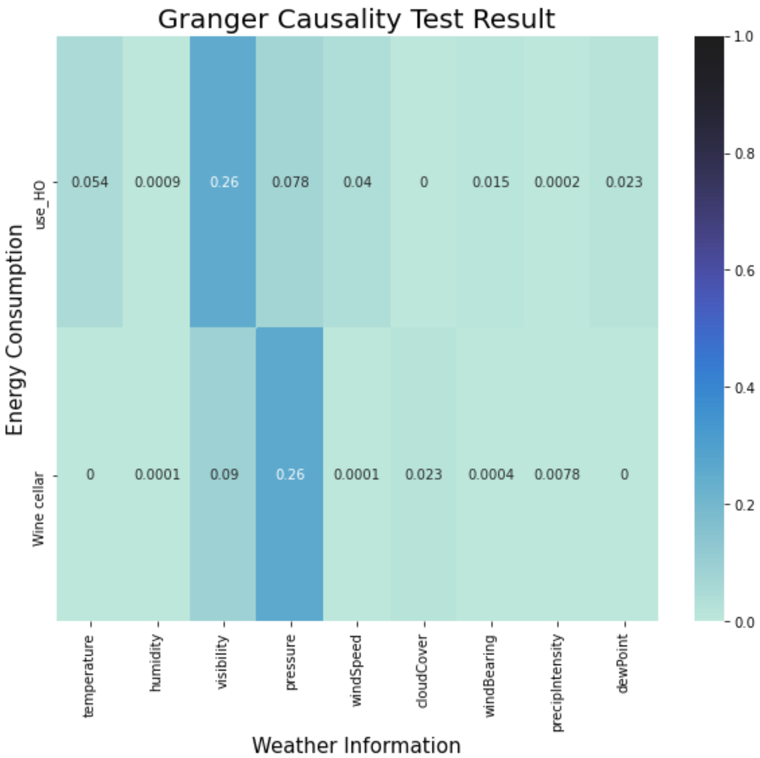


Fig 4.12 Granger Casuality Test Result

In fig 4.12, This heatmap visualizes the p-values for testing the null hypothesis that the correlation between variable pairs is zero. Lower p-values (closer to zero) indicate statistically significant correlations, meaning there's a stronger evidence of association between variables. The color gradient emphasizes the degree of significance, where the lighter regions represent non-significant relationships (higher p-values), and the darker regions highlight significant correlations (low p-values).

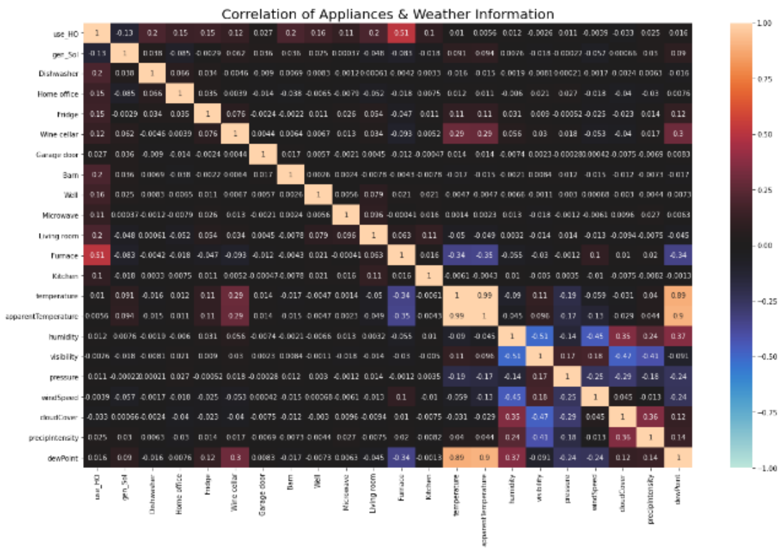


Fig 4.13 Correlation for Appliances and Weather Information

The fig 4.13 shows a correlation heatmap, where the colors indicate the strength and direction of relationships between variables. Lighter colors (yellow/orange) represent strong positive correlations, while darker colors (purple/blue) represent strong negative correlations. Values closer to 1 or -1 signify stronger correlations, either positively or negatively, while values closer to 0 suggest weaker or no correlations. Diagonal elements are always 1, as they represent self-correlations. Notable blocks of both positive and negative correlations are evident, highlighting relationships between certain clusters of variables. This visualization is useful for identifying patterns of interaction between variables.

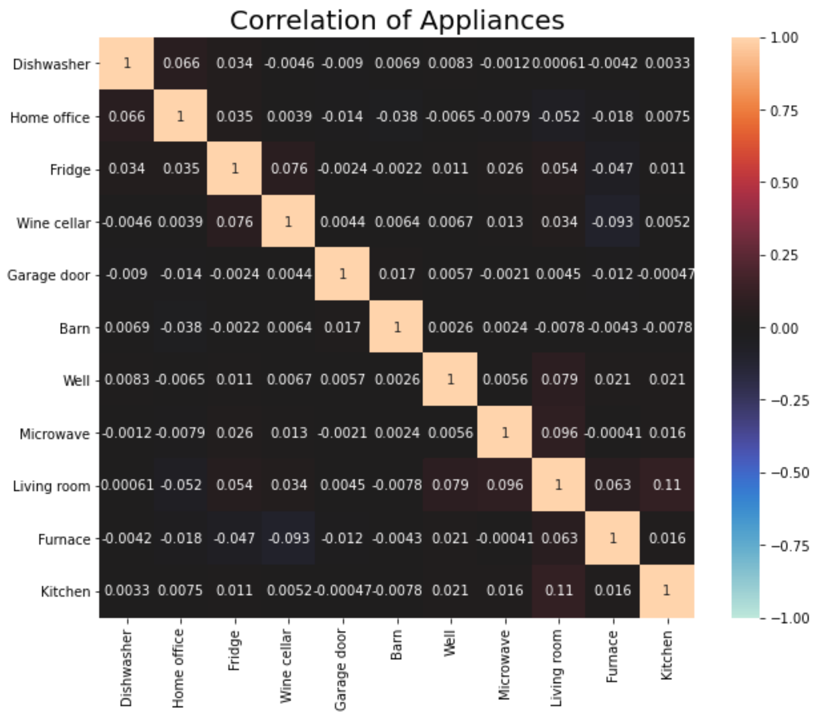


Fig 4.14 Correlation of Appliances

The fig 4.14 is also a correlation heatmap but appears to involve fewer variables than the first one. Similar to the previous one, it represents the relationships between pairs of variables, where lighter shades (closer to yellow) indicate stronger positive correlations and darker shades (closer to blue or purple) indicate negative correlations. Here, the correlations seem to be relatively weak across most variables, with values close to zero dominating the matrix, indicating minimal linear relationships between these variables. The diagonal values are all 1, reflecting self-correlations. This matrix suggests that the variables do not have strong linear interdependencies.

5. CONCLUSION:

This project has explored the transformative potential of smart home technologies in optimizing household energy consumption. By employing advanced machine learning models and neural networks, the study has successfully predicted energy usage patterns based on historical data and various influencing factors such as weather conditions, occupancy, and appliance usage. The accurate forecasting capabilities demonstrated by these models highlight their effectiveness in enabling proactive energy management, which can lead to significant reductions in energy costs and consumption.

The relevance of this research is underscored by the growing need for energy efficiency and sustainability in response to global environmental challenges. Smart home systems, equipped with predictive analytics and automation features, empower users to make informed decisions about their energy use, reducing waste and contributing to a smaller carbon footprint. For utility companies, the ability to anticipate household energy demand facilitates better grid management and enhances overall energy supply reliability, which is crucial for preventing overloads and ensuring stable service delivery.

Moreover, the study provides valuable insights into the practical applications of these technologies in smart home systems and demand response programs. By automating energy-saving measures—such as adjusting heating and cooling based on occupancy or turning off unused appliances—these systems not only optimize energy use but also improve user comfort and convenience. This integration of technology into daily life represents a significant shift toward more sustainable living practices.

The findings of this research also have important implications for policymakers and energy planners. The data-driven approach demonstrated in this study can inform the development of strategies aimed at promoting energy efficiency at a broader scale. Encouraging the adoption of smart home technologies through incentives and awareness programs could accelerate the transition to more sustainable energy use patterns.

In conclusion, this project has made a meaningful contribution to the field of energy management by bridging the gap between academic research and real-world applications. The implementation of smart home technologies for energy optimization is not only feasible but also essential for meeting the dual goals of reducing energy costs and mitigating environmental impact. As the technology continues to evolve, future research should focus on enhancing the integration of these systems with renewable energy sources and exploring their potential in different residential settings. Such advancements will further strengthen the role of smart homes in promoting energy sustainability and fostering a more efficient and eco-friendly future.

5.1 SCOPE FOR FURTHER ENHANCEMENT

While this project has successfully demonstrated the potential of smart home technologies in optimizing energy consumption, several avenues remain open for future enhancement. One promising area is the integration of renewable energy sources, such as solar panels or wind turbines, with smart home systems. By incorporating real-time energy production data from these sources, households can maximize their use of clean energy, further reducing dependence on the grid and lowering carbon emissions.

Another significant enhancement would be the development of more sophisticated predictive models. Future research could focus on incorporating additional data points, such as real-time electricity prices, detailed appliance usage patterns, and behavioral data, to refine energy consumption predictions. The use of advanced machine learning techniques, like deep learning and reinforcement learning, could also improve the accuracy and adaptability of these models, allowing for more personalized and responsive energy management solutions.

The expansion of smart home capabilities beyond energy management is another exciting direction. Integrating other smart home features, such as security systems, water management, and indoor air quality monitoring, could create a holistic home automation system that not only optimizes energy use but also enhances overall household efficiency, safety, and comfort.

Furthermore, the scalability and interoperability of smart home systems should be addressed to support widespread adoption. Developing standardized protocols and frameworks that ensure seamless integration between different devices and platforms will be crucial for enabling cohesive and user-friendly smart home ecosystems. This would also allow for the creation of community-level energy management solutions, where multiple households collaborate to optimize collective energy use and contribute to grid stability.

Lastly, expanding the application of smart home technologies to diverse residential and commercial settings can provide valuable insights into their performance in various environments. Future research should explore their effectiveness in multi-family residences, office buildings, and industrial facilities, tailoring solutions to meet the specific energy needs and challenges of these contexts.

By pursuing these enhancements, the potential of smart home technologies to transform energy consumption practices and contribute to a more sustainable future can be fully realized.

6. BIBLIOGRAPHY

1. Abu Gunmi Mohammad, Feihu Hu, Diana Abu-Ghunmi, Lina Abu-Ghunmi [2024], “A smart home energy management system methodology for techno-economic optimal sizing of standalone renewable-storage power systems under uncertainties” 1-7

2. AL Sultan, Yasser, Ben Salma Sami, Bassam A. Zafar [2021], “Smart Home Energy Management System”, Vol. 12, No. 3

3. Büyük, Mehmet, Ercan Avşar, & Mustafa İnci [2022], “Overview of smart home concepts through energy management systems, numerical research, and future perspective” 1-8

4. Fiorini, Laura, & Marco Aiello [2022], “Automatic optimal multi-energy management of smart homes”, 1-20

5. Gunmi, Mohammad Abu, Feihu Hu, Diana Abu-Ghunmi, Lina Abu-Ghunmi [2024], “A smart home energy management system methodology for techno-economic optimal sizing of standalone renewable-storage power systems under uncertainties” 1-7

6. Hasan, Mehidi, Touhidul Islam Talukder, Fatema Tauze Zohora Saima, MD. Nazim Uddin Joy, Adrik Das, MD. Nursari Hasan Sheham [2022], “Smart Home Automation System Powered by Renewable Energy” 1-10

7. Hassan, Heba, Salah Kamel, & Mohamed H. Hassan [2023], “Smart home energy management and power trading optimization using an enhanced manta ray foraging optimization” 1-25

8. Jensen, Rikke Hagensby, Yolande Strengers, Jesper Kjeldskov, Larissa Nicholls, Mikael B. Skov [2018], “Designing the Desirable Smart Home: A Study of Household Experiences and Energy Consumption Impacts” 1-15

9. Kanade, S. G., & Asha K. Bhise [2022], “Artificial Intelligence Based Smart Home Energy Management System: A Review” Volume: 06 Issue: 12

10. Lashkari, Behzad, Yuxiang Chen, and Petr Musilek [2019], “Energy Management for Smart Homes—State of the Art”, 1-23

11. Lingaraja, D, S. Praveen Kumar, T. Aravind, T. K. Srinivasan, G. Dinesh Ram, & S. Ramya [2023], “Design of Solar Energy Harvester for Smart Home Application”, 1-19

12. Liska, Martin, Marian Ivanic, Vladimir Volcko, & Peter Janiga [2015], “Research on Smart Home Energy Management System” 1-7

13. Ma, Yunlong, Xiao Chen, Liming Wang, & Jianlan Yang [2021], “Investigation of Smart Home Energy Management System for Demand Response Application” 1-10

14. Mubdir, Bilal, Asaad Al-Hindawi, Iraq Noor Hadi [2016], “Design of Smart Home Energy Management System for Saving Energy” 1-16

15. Muhammad Akbar, Nur Insaan, Zulkifli Tahir, & Andani [2023], “Performance Analysis of Fog Architecture to Monitor Solar Panel for Smart Home”, 1-45

16. Nassereddine, M., J. Rizk, A. Hellany, & M. Nagrial [2016], “Electrical Energy Management for Advance Smart Home Systems: Introduction” 1-7

17. Park, Eung-Suk, ByungYong Hwang, Kyungwan Ko, & Daecheol Kim [2017], “Consumer Acceptance Analysis of the Home Energy Management System” 1-15

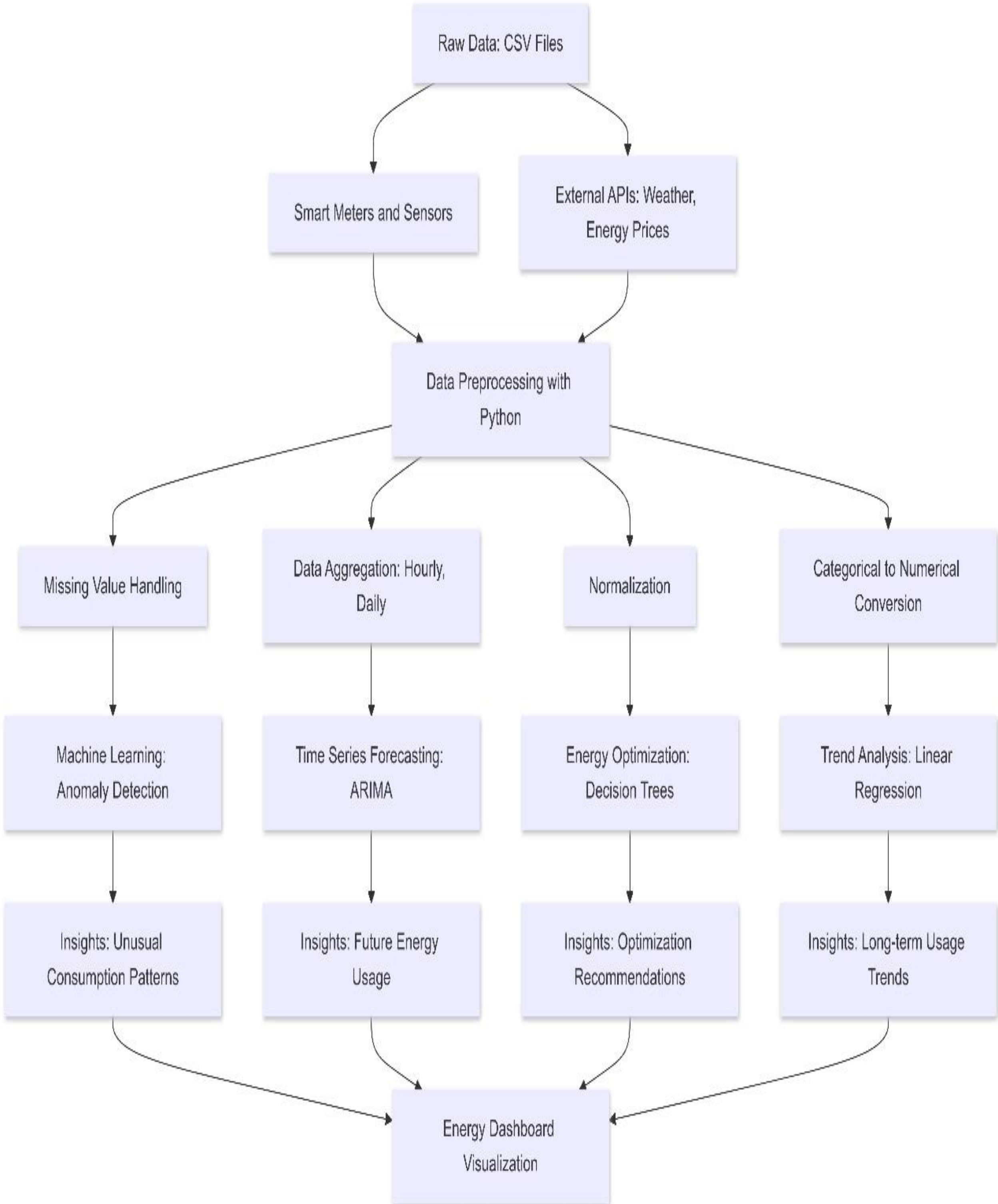
18. Raza, Ali, Li Jingzhao, Yazeed Ghadi, Muhammad Adnan, & Mansoor Ali [2024], “Smart home energy management systems: Research challenges and survey” 1-54

19. Siswipraptini, Puji Catur, Rosida Nur Aziza, Riki Ruli A. Siregar, & Arief Ramadhan [2024], “Smart Home Energy Management Systems: A Systematic Review of Architecture, Communication, and Algorithmic Trends” Vol. 14, 129-146

20. Zipperer, Adam, Patricia A. Aloise-Young, Siddharth Suryanarayanan, Robin Roche, Lieko Earle, Dane Christensen, Pablo Bauleo, & Daniel Zimmerle [2013], “Electric Energy Management in the Smart Home: Perspectives on Enabling Technologies and Consumer Behavior” 1-13

7. APPENDICES:

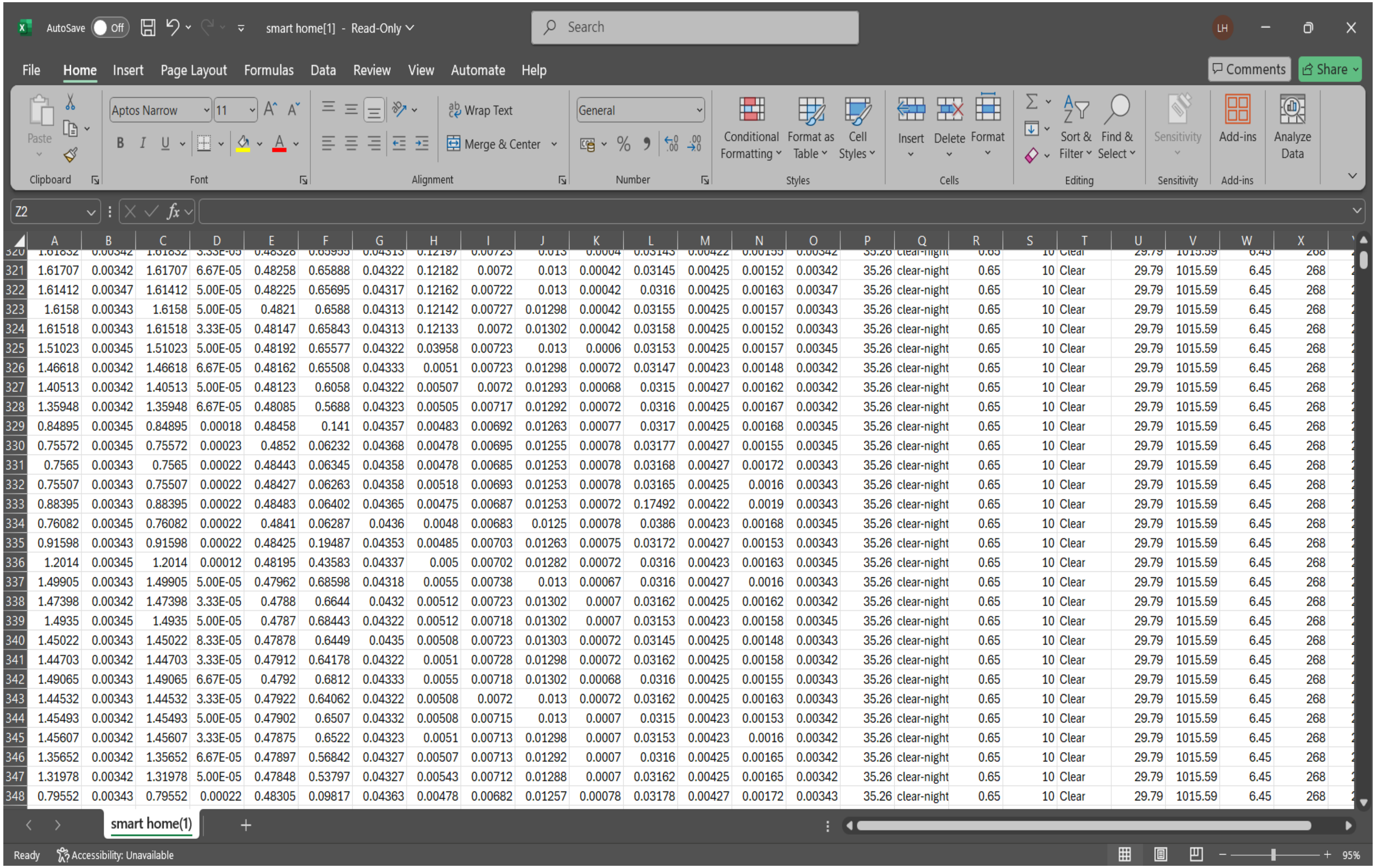
A. Data flow diagram:



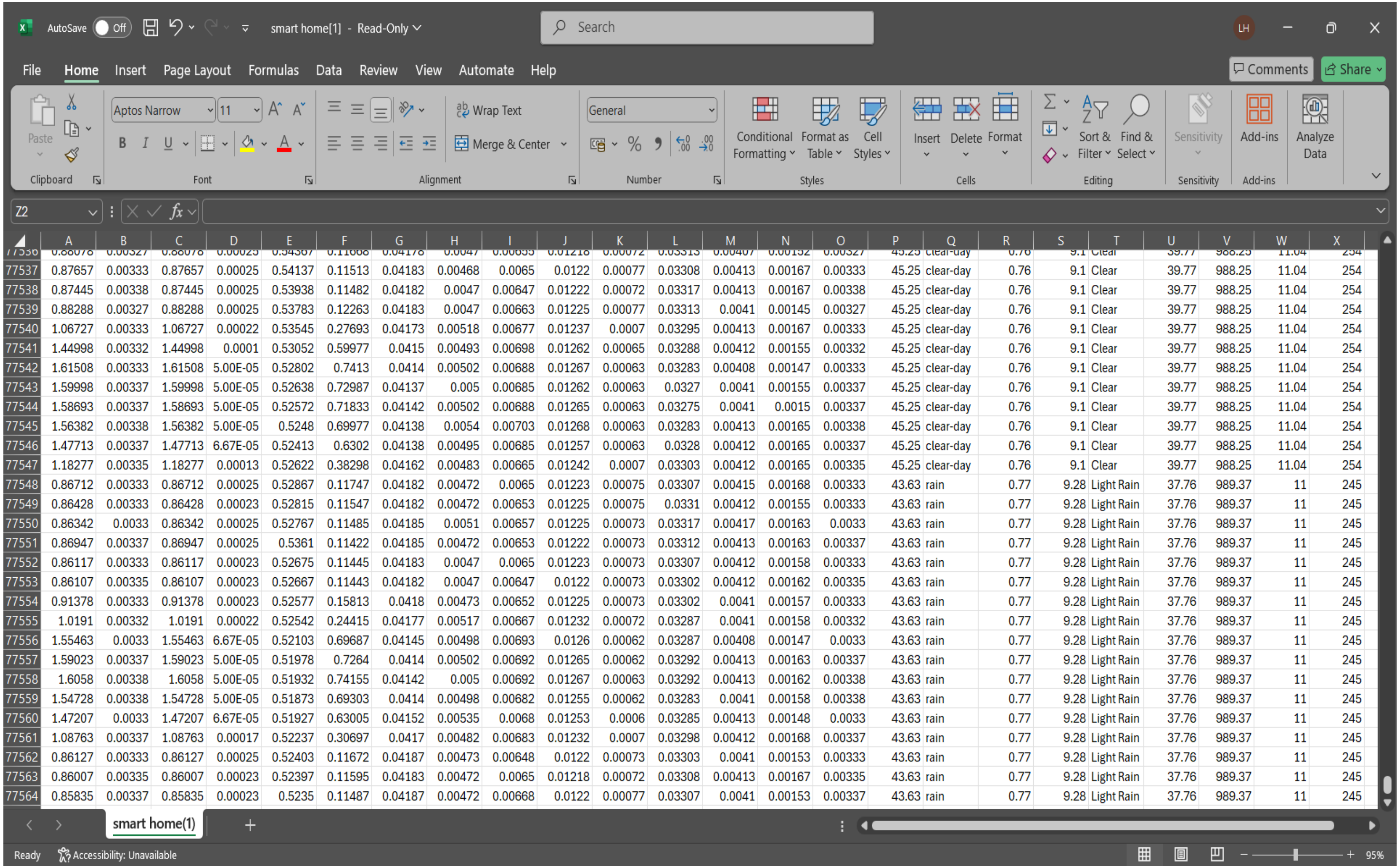
B. Table structure:

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA
1	use [kW]	gen [kW]	House over	Dishwashe	Furnace 1 [	Furnace 2 [	Home offic	Fridge [kW]	Wine cellar	Garage doc	Kitchen 12	Barn [kW]	Microwave	Living roon	Solar [kW]	temperatur	icon	humidity	visibility	summary	apparentTe	pressure	windSpeed	windBearir	dewPoint	Predicted House O	
2	0.9328333	0.0034833	0.9328333	3.33E-05	0.0207	0.0619167	0.4426333	0.12415	0.0069833	0.0130833	0.0004167	0.03135	0.0040667	0.0015167	0.0034833	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	0.9363167	
3	0.9343333	0.0034667	0.9343333	0	0.0207167	0.0638167	0.4440667	0.124	0.0069833	0.0131167	0.0004167	0.0315	0.0040667	0.00165	0.0034667	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	0.9378	
4	0.9318167	0.0034667	0.9318167	1.67E-05	0.0207	0.0623167	0.4460667	0.1235333	0.0069833	0.0130833	0.0004333	0.0315167	0.0040667	0.00165	0.0034667	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	0.9352833	
5	1.02205	0.0034833	1.02205	1.67E-05	0.1069	0.0685167	0.4465833	0.1231333	0.0069833	0.013	0.0004333	0.0315	0.0040667	0.0016167	0.0034833	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	1.0255333	
6	1.1394	0.0034667	1.1394	0.0001333	0.2369333	0.0639833	0.4465333	0.12285	0.00685	0.0127833	0.00045	0.0315	0.0040667	0.0015833	0.0034667	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	1.1428667	
7	1.3918667	0.0034333	1.3918667	0.0002833	0.50325	0.0636667	0.4470333	0.1223	0.0067167	0.0124333	0.0004833	0.03145	0.0040667	0.0015833	0.0034333	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	1.3953	
8	1.3662167	0.00345	1.3662167	0.0002833	0.4994	0.0637167	0.4432667	0.12205	0.0067333	0.0124167	0.0005167	0.03155	0.0041167	0.0015333	0.00345	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	1.3696667	
9	1.4319	0.0034167	1.4319	0.00025	0.4778667	0.1786333	0.4442833	0.1218	0.0067833	0.01255	0.0004833	0.0317333	0.0042	0.00155	0.0034167	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	1.4353167	
10	1.6273	0.0034167	1.6273	0.0001833	0.44765	0.3657	0.4414667	0.1216167	0.00695	0.0127167	0.0004667	0.0317667	0.0042	0.0015667	0.0034167	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	1.6307167	
11	1.7353833	0.0034167	1.7353833	1.67E-05	0.17155	0.6825	0.4387333	0.1216333	0.0072333	0.01335	0.0003667	0.0316667	0.0042	0.0016167	0.0034167	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	1.7388	
12	1.5850833	0.0034167	1.5850833	5.00E-05	0.0221	0.6787333	0.4402	0.12145	0.0074333	0.0135833	0.00035	0.0316667	0.0042	0.0015667	0.0034167	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	1.5885	
13	1.5103167	0.0034333	1.5103167	3.33E-05	0.0219667	0.6206667	0.43695	0.12125	0.0073167	0.0135333	0.0003333	0.03175	0.0042	0.0015667	0.0034333	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	1.51375	
14	1.4598667	0.00345	1.4598667	5.00E-05	0.0218833	0.5774667	0.43995	0.1210333	0.0072333	0.0135167	0.0003667	0.0317833	0.0042167	0.0015833	0.00345	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	1.4633167	
15	0.8405833	0.0034333	0.8405833	0	0.02095	0.1448	0.4447833	0.0350167	0.0070333	0.0131833	0.00065	0.0317833	0.0042167	0.0016167	0.0034333	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	0.8440167	
16	0.7032	0.0034333	0.7032	1.67E-05	0.0207333	0.0619667	0.4438333	0.0047833	0.0069667	0.0131167	0.0007333	0.03175	0.0042333	0.00155	0.0034333	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	0.7066333	
17	0.5718833	0.00345	0.5718833	0	0.02065	0.06365	0.3077833	0.0049167	0.00705	0.0131	0.0007333	0.0317333	0.0042167	0.0015833	0.00345	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	0.5753333	
18	0.4857333	0.00345	0.4857333	1.67E-05	0.0206167	0.0634333	0.22045	0.0049833	0.0070333	0.0131167	0.00075	0.0318333	0.0042333	0.0016167	0.00345	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	0.4891833	
19	0.5231667	0.0034333	0.5231667	0	0.0206333	0.0621167	0.26005	0.00495	0.007	0.0130833	0.0007333	0.03185	0.00425	0.0017167	0.0034333	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	0.5266	
20	0.5362	0.00345	0.5362	0	0.0206833	0.0629167	0.2720667	0.00495	0.0070333	0.01315	0.0007333	0.0318667	0.0042333	0.00165	0.00345	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	0.53965	
21	0.53415	0.00345	0.53415	1.67E-05	0.0206667	0.06265	0.2700667	0.00495	0.0071	0.01315	0.0007333	0.0319	0.0042333	0.00175	0.00345	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	0.5376	
22	0.5338167	0.00345	0.5338167	0	0.0206333	0.0629667	0.2700333	0.00495	0.0070333	0.0131167	0.00075	0.0318167	0.0042333	0.0015667	0.00345	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	0.5372667	
23	0.5236333	0.00345	0.5236333	1.67E-05	0.02055	0.0632833	0.2598167	0.00495	0.0070333	0.0130833	0.0007333	0.0317333	0.0042167	0.0016667	0.00345	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	0.5270833	
24	0.57725	0.0034167	0.57725	0	0.0206833	0.10975	0.257	0.0049833	0.0070667	0.0131333	0.0007333	0.0316833	0.0042333	0.0015167	0.0034167	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	0.5806667	
25	0.6795667	0.0034333	0.6795667	1.67E-05	0.0208667	0.1940833	0.2571	0.0050167	0.0071167	0.0132	0.0007	0.0317167	0.0042167	0.00165	0.0034333	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	0.683	
26	1.2931667	0.0034	1.2931667	1.67E-05	0.1074333	0.6224667	0.2541	0.0052	0.00725	0.01335	0.00065	0.0315667	0.0042	0.0015667	0.0034	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	1.2965667	
27	1.5466667	0.0034333	1.5466667	1.67E-05	0.2205667	0.68005	0.2539333	0.00555	0.0072667	0.0131833	0.0007	0.0310667	0.0041667	0.00165	0.0034333	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	1.5501	
28	1.82235	0.0034167	1.82235	6.67E-05	0.49665	0.677	0.2545333	0.0049167	0.0071	0.0127833	0.0007167	0.0309667	0.0100667	0.0016	0.0034167	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	1.8257667	
29	2.6425167	0.0020333	2.6425167	8.33E-05	0.49875	0.5755667	0.2555333	0.0045667	0.0070333	0.0126667	0.0004	0.0880667	1.0407667	0.0013667	0.0020333	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	2.64455	
30	1.73935	0.0031333	1.73935	0.0001	0.49445	0.48835	0.2558167	0.00475	0.0070167	0.0127167	0.0006167	0.1135167	0.0043833	0.0015833	0.0031333	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	1.7424833	
31	1.1872	0.0030833	1.1872	0.00025	0.4538167	0.0628833	0.2560333	0.0045667	0.0247167	0.0125	0.0007	0.0317667	0.0045	0.0011667	0.0030833	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	1.1902833	
32	1.19095	0.0030833	1.19095	0.0002167	0.3874	0.0618833	0.2568667	0.0049333	0.1017833	0.0125333	0.0007	0.03175	0.0045	0.00115	0.0030833	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	1.1940333	
33	0.8330833	0.0030667	0.8330833	1.67E-05	0.02065	0.0630667	0.2545833	0.0048167	0.0971833	0.0130167	0.0006667	0.03175	0.0045	0.0011667	0.0030667	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	0.83615	
34	0.8342833	0.0030667	0.8342833	0	0.0206167	0.0620333	0.25655	0.0048167	0.1008333	0.0130333	0.0006667	0.0317333	0.0045167	0.0012	0.0030667	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	0.83735	
35	0.8404333	0.0030667	0.8404333	1.67E-05	0.0206	0.06265	0.2560167	0.0048167	0.10915	0.0130333	0.00065	0.0316833	0.0045	0.0011833	0.0030667	36.14	clear-night	0.62	10	Clear	29.26	1016.91	9.18	282	24.4	0.8435	

smart_home(1) +



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X
321	1.61707	0.00342	1.61707	6.67E-05	0.48258	0.65888	0.04322	0.12182	0.0072	0.013	0.00042	0.03145	0.00425	0.00152	0.00342	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
322	1.61412	0.00347	1.61412	5.00E-05	0.48225	0.65695	0.04317	0.12162	0.00722	0.013	0.00042	0.0316	0.00425	0.00163	0.00347	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
323	1.6158	0.00343	1.6158	5.00E-05	0.4821	0.6588	0.04313	0.12142	0.00727	0.01298	0.00042	0.03155	0.00425	0.00157	0.00343	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
324	1.61518	0.00343	1.61518	3.33E-05	0.48147	0.65843	0.04313	0.12133	0.0072	0.01302	0.00042	0.03158	0.00425	0.00152	0.00343	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
325	1.51023	0.00345	1.51023	5.00E-05	0.48192	0.65577	0.04322	0.03958	0.00723	0.013	0.0006	0.03153	0.00425	0.00157	0.00345	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
326	1.46618	0.00342	1.46618	6.67E-05	0.48162	0.65508	0.04333	0.0051	0.00723	0.01298	0.00072	0.03147	0.00423	0.00148	0.00342	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
327	1.40513	0.00342	1.40513	5.00E-05	0.48123	0.6058	0.04322	0.00507	0.0072	0.01293	0.00068	0.0315	0.00427	0.00162	0.00342	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
328	1.35948	0.00342	1.35948	6.67E-05	0.48085	0.5688	0.04323	0.00505	0.00717	0.01292	0.00072	0.0316	0.00425	0.00167	0.00342	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
329	0.84895	0.00345	0.84895	0.00018	0.48458	0.141	0.04357	0.00483	0.00692	0.01263	0.00077	0.0317	0.00425	0.00168	0.00345	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
330	0.75572	0.00345	0.75572	0.00023	0.4852	0.06232	0.04368	0.00478	0.00695	0.01255	0.00078	0.03177	0.00427	0.00155	0.00345	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
331	0.7565	0.00343	0.7565	0.00022	0.48443	0.06345	0.04358	0.00478	0.00685	0.01253	0.00078	0.03168	0.00427	0.00172	0.00343	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
332	0.75507	0.00343	0.75507	0.00022	0.48427	0.06263	0.04358	0.00518	0.00693	0.01253	0.00078	0.03165	0.00425	0.0016	0.00343	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
333	0.88395	0.00343	0.88395	0.00022	0.48483	0.06402	0.04365	0.00475	0.00687	0.01253	0.00072	0.17492	0.00422	0.0019	0.00343	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
334	0.76082	0.00345	0.76082	0.00022	0.4841	0.06287	0.0436	0.0048	0.00683	0.0125	0.00078	0.0386	0.00423	0.00168	0.00345	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
335	0.91598	0.00343	0.91598	0.00022	0.48425	0.19487	0.04353	0.00485	0.00703	0.01263	0.00075	0.03172	0.00427	0.00153	0.00343	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
336	1.2014	0.00345	1.2014	0.00012	0.48195	0.43583	0.04337	0.005	0.00702	0.01282	0.00072	0.0316	0.00423	0.00163	0.00345	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
337	1.49905	0.00343	1.49905	5.00E-05	0.47962	0.68598	0.04318	0.0055	0.00738	0.013	0.00067	0.0316	0.00427	0.0016	0.00343	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
338	1.47398	0.00342	1.47398	3.33E-05	0.4788	0.6644	0.0432	0.00512	0.00723	0.01302	0.0007	0.03162	0.00425	0.00162	0.00342	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
339	1.4935	0.00345	1.4935	5.00E-05	0.4787	0.68443	0.04322	0.00512	0.00718	0.01302	0.0007	0.03153	0.00423	0.00158	0.00345	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
340	1.45022	0.00343	1.45022	8.33E-05	0.47878	0.6449	0.0435	0.00508	0.00723	0.01303	0.00072	0.03145	0.00425	0.00148	0.00343	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
341	1.44703	0.00342	1.44703	3.33E-05	0.47912	0.64178	0.04322	0.0051	0.00728	0.01298	0.00072	0.03162	0.00425	0.00158	0.00342	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
342	1.49065	0.00343	1.49065	6.67E-05	0.4792	0.6812	0.04333	0.0055	0.00718	0.01302	0.00068	0.0316	0.00425	0.00155	0.00343	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
343	1.44532	0.00343	1.44532	3.33E-05	0.47922	0.64062	0.04322	0.00508	0.0072	0.013	0.00072	0.03162	0.00425	0.00163	0.00343	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
344	1.45493	0.00342	1.45493	5.00E-05	0.47902	0.6507	0.04332	0.00508	0.00715	0.013	0.0007	0.0315	0.00423	0.00153	0.00342	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
345	1.45607	0.00342	1.45607	3.33E-05	0.47875	0.6522	0.04323	0.0051	0.00713	0.01298	0.0007	0.03153	0.00423	0.0016	0.00342	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
346	1.35652	0.00342	1.35652	6.67E-05	0.47897	0.56842	0.04327	0.00507	0.00713	0.01292	0.0007	0.0316	0.00425	0.00165	0.00342	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
347	1.31978	0.00342	1.31978	5.00E-05	0.47848	0.53797	0.04327	0.00543	0.00712	0.01288	0.0007	0.03162	0.00425	0.00165	0.00342	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268
348	0.79552	0.00343	0.79552	0.00022	0.48305	0.09817	0.04363	0.00478	0.00682	0.01257	0.00078	0.03178	0.00427	0.00172	0.00343	35.26	clear-night	0.65	10	Clear	29.79	1015.59	6.45	268



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X
77537	0.87657	0.00333	0.87657	0.00025	0.54137	0.11513	0.04183	0.00468	0.0065	0.0122	0.00077	0.03308	0.00413	0.00167	0.00333	45.25	clear-day	0.76	9.1	Clear	39.77	988.25	11.04	254
77538	0.87445	0.00338	0.87445	0.00025	0.53938	0.11482	0.04182	0.0047	0.00647	0.01222	0.00072	0.03317	0.00413	0.00167	0.00338	45.25	clear-day	0.76	9.1	Clear	39.77	988.25	11.04	254
77539	0.88288	0.00327	0.88288	0.00025	0.53783	0.12263	0.04183	0.0047	0.00663	0.01225	0.00077	0.03313	0.0041	0.00145	0.00327	45.25	clear-day	0.76	9.1	Clear	39.77	988.25	11.04	254
77540	1.06727	0.00333	1.06727	0.00022	0.53545	0.27693	0.04173	0.00518	0.00677	0.01237	0.0007	0.03295	0.00413	0.00167	0.00333	45.25	clear-day	0.76	9.1	Clear	39.77	988.25	11.04	254
77541	1.44998	0.00332	1.44998	0.0001	0.53052	0.59977	0.0415	0.00493	0.00698	0.01262	0.00065	0.03288	0.00412	0.00155	0.00332	45.25	clear-day	0.76	9.1	Clear	39.77	988.25	11.04	254
77542	1.61508	0.00333	1.61508	5.00E-05	0.52802	0.7413	0.0414	0.00502	0.00688	0.01267	0.00063	0.03283	0.00408	0.00147	0.00333	45.25	clear-day	0.76	9.1	Clear	39.77	988.25	11.04	254
77543	1.59998	0.00337	1.59998	5.00E-05	0.52638	0.72987	0.04137	0.005	0.00685	0.01262	0.00063	0.0327	0.0041	0.00155	0.00337	45.25	clear-day	0.76	9.1	Clear	39.77	988.25	11.04	254
77544	1.58693	0.00337	1.58693	5.00E-05	0.52572	0.71833	0.04142	0.00502	0.00688	0.01265	0.00063	0.03275	0.0041	0.0015	0.00337	45.25	clear-day	0.76	9.1	Clear	39.77	988.25	11.04	254
77545	1.56382	0.00338	1.56382	5.00E-05	0.5248	0.69977	0.04138	0.0054	0.00703	0.01268	0.00063	0.03283	0.00413	0.00165	0.00338	45.25	clear-day	0.76	9.1	Clear	39.77	988.25	11.04	254
77546	1.47713	0.00337	1.47713	6.67E-05	0.52413	0.6302	0.04138	0.00495	0.00685	0.01257	0.00063	0.0328	0.00412	0.00165	0.00337	45.25	clear-day	0.76	9.1	Clear	39.77	988.25	11.04	254
77547	1.18277	0.00335	1.18277	0.00013	0.52622	0.38298	0.04162	0.00483	0.00665	0.01242	0.0007	0.03303	0.00412	0.00165	0.00335	45.25	clear-day	0.76	9.1	Clear	39.77	988.25	11.04	254
77548	0.86712	0.00333	0.86712	0.00025	0.52867	0.11747	0.04182	0.00472	0.0065	0.01223	0.00075	0.03307	0.00415	0.00168	0.00333	43.63	rain	0.77	9.28	Light Rain	37.76	989.37	11	245
77549	0.86428	0.00333	0.86428	0.00023	0.52815	0.11547	0.04182	0.00472	0.00653	0.01225	0.00075	0.0331	0.00412	0.00155	0.00333	43.63	rain	0.77	9.28	Light Rain	37.76	989.37	11	245
77550	0.86342	0.0033	0.86342	0.00025	0.52767	0.11485	0.04185	0.0051	0.00657	0.01225	0.00073	0.03317	0.00417	0.00163	0.0033	43.63	rain	0.77	9.28	Light Rain	37.76	989.37	11	245
77551	0.86947	0.00337	0.86947	0.00025	0.5361	0.11422	0.04185	0.00472	0.00653	0.01222	0.00073	0.03312	0.00413	0.00163	0.00337	43.63	rain	0.77	9.28	Light Rain	37.76	989.37	11	245
77552	0.86117	0.00333	0.86117	0.00023	0.52675	0.11445	0.04183	0.0047	0.0065	0.01223	0.00073	0.03307	0.00412	0.00158	0.00333	43.63	rain	0.77	9.28	Light Rain	37.76	989.37	11	245
77553	0.86107	0.00335	0.86107	0.00023	0.52667	0.11443	0.04182	0.0047	0.00647	0.0122	0.00073	0.03302	0.00412	0.00162	0.00335	43.63	rain	0.77	9.28	Light Rain	37.76	989.37	11	245
77554	0.91378	0.00333	0.91378	0.00023	0.52577	0.15813	0.0418	0.00473	0.00652	0.01225	0.00073	0.03302	0.0041	0.00157	0.00333	43.63	rain	0.77	9.28	Light Rain	37.76	989.37	11	245
77555	1.0191	0.00332	1.0191	0.00022	0.52542	0.24415	0.04177	0.00517	0.00667	0.01232	0.00072	0.03287	0.0041	0.00158	0.00332	43.63	rain	0.77	9.28	Light Rain	37.76	989.37	11	245
77556	1.55463	0.0033	1.55463	6.67E-05	0.52103	0.69687	0.04145	0.00498	0.00693	0.0126	0.00062	0.03287	0.00408	0.00147	0.0033	43.63	rain	0.77	9.28	Light Rain	37.76	989.37	11	245
77557	1.59023	0.00337	1.59023	5.00E-05	0.51978	0.7264	0.0414	0.00502	0.00692	0.01265	0.00062	0.03292	0.00413	0.00163	0.00337	43.63	rain	0.77	9.28	Light Rain	37.76	989.37	11	245
77558	1.6058	0.00338	1.6058	5.00E-05	0.51932	0.74155	0.04142	0.005	0.00692	0.01267	0.00063	0.03292	0.00413	0.00162	0.00338	43.63	rain	0.77	9.28	Light Rain	37.76	989.37	11	245
77559	1.54728	0.00338	1.54728	5.00E-05	0.51873	0.69303	0.0414	0.00498	0.00682	0.01255	0.00062	0.03283	0.0041	0.00158	0.00338	43.63	rain	0.77	9.28	Light Rain	37.76	989.37	11	245
77560	1.47207	0.0033	1.47207	6.67E-05	0.51927	0.63005	0.04152	0.00535	0.0068	0.01253	0.0006	0.03285	0.00413	0.00148	0.0033	43.63	rain	0.77	9.28	Light Rain	37.76	989.37	11	245
77561	1.08763	0.00337	1.08763	0.00017	0.52237	0.30697	0.0417	0.00482	0.00683	0.01232	0.0007	0.03298	0.00412	0.00168	0.00337	43.63	rain	0.77	9.28	Light Rain	37.76	989.37	11	245
77562	0.86127	0.00333	0.86127	0.00025	0.52403	0.11672	0.04187	0.00473	0.00648	0.0122	0.00073	0.03303	0.0041	0.00153	0.00333	43.63	rain	0.77	9.28	Light Rain	37.76	989.37	11	245
77563	0.86007	0.00335	0.86007	0.00023	0.52397	0.11595	0.04183	0.00472	0.0065	0.01218	0.00072	0.03308	0.00413	0.00167	0.00335	43.63	rain	0.77	9.28	Light Rain	37.76	989.37	11	245
77564	0.85835	0.00337	0.85835	0.00023	0.5235	0.11487	0.04187	0.00472	0.00668	0.0122	0.00077	0.03307	0.0041	0.00153	0.00337	43.63	rain	0.77	9.28	Light Rain	37.76	989.37	11	245

C. SAMPLE CODING:

```
import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

# Load the dataset

file_path = '/path/to/your/smart_home.csv'

data = pd.read_csv(file_path)

# Display the first few rows of the dataset

print(data.head())

# Step 1: Data Preprocessing

if 'timestamp' in data.columns:

    data[' House overall [kW]'] = pd.to_datetime(data[' House overall [kW]'])


# Check for missing values and fill them

missing_data = data.isnull().sum()

print(f"Missing data:\n{missing_data}")


# Fill missing values with the mean of the respective column

data.fillna(data.mean(), inplace=True)

# Step 2: Basic Data Aggregation (Example: Daily Energy Consumption)

if 'use [kW]' in data.columns:

    daily_data = data.resample('D', on=' House overall [kW]').sum()

    print(daily_data.head())

# Step 3: Visualization

plt.figure(figsize=(10, 6))

sns.lineplot(data=daily_data, x=' House overall [kW]', y='use [kW]')

plt.title('Daily Energy Consumption')

plt.xlabel('Date')

plt.ylabel('Energy Usage (kW)')
```

```
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
# Step 4: Analysis - Correlation between Environmental Factors and Energy Usage
if 'temperature' in data.columns and 'use [kW]' in data.columns:
   plt.figure(figsize=(10, 6))
   sns.scatterplot(x=data['temperature'], y=data['use [kW]'])
   plt.title('Energy Usage vs Temperature')
   plt.xlabel('Temperature (°C)')
   plt.ylabel('Energy Usage (kW)')
   plt.tight_layout()
   plt.show()
```