NOVA SCHOOL OF
SCIENCE & TECHNOLOGY

DEPARTMENT OF ELECTRICAL
AND COMPUTER ENGINEERING

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Master in Electrical and Computer Engineering

INTELLIGENT SYSTEM FOR OPTIMIZING PHOTOVOLTAIC INSTALLATIONS: TARIFF CONTROL STRATEGIES AND REUSE OF SECOND LIFE BATTERIES

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Lastly, I would like to thank my family for helping me to complete this stage of my life, and my closest friends for their support and entertainment.

ABSTRACT

We are moving towards an increasingly autonomous world, always seeking to take full advantage of developed technologies, as is the case with photovoltaic installations in homes. The majority of people aim to harness solar energy to power their residences, vehicles, or even contribute to the creation of electric communities for enhanced energy efficiency and assistance in "decarbonisation".

The challenge arises when solar energy is not available, but there is a need for consumption. In other words, when there is no sun, there is no energy available for consumption in an autonomous perspective. A solar battery seems to be the most obvious solution but brings associated problems, such as a substantial initial investment, making the issue of photovoltaic panels challenging. Thus, there arises a need to find solutions. The goal of this dissertation is to develop a system capable of controlling a domestic photovoltaic installation with a solar battery and capable of adopting methods to achieve a return on investment. These methods include controlling energy tariffs and utilizing second life batteries, which are batteries used in electric cars that are no longer considered ideal for maintaining the car's performance due to the state of health reaching less than 80%.

This thesis outlines the development of an intelligent system, ***WattFuture***, designed to oversee a photovoltaic installation incorporating solar batteries. To achieve this, artificial intelligent models are deployed to predict energy values, including production and consumption. The integration of application programming interfaces, APIs, providing weather information is necessary for more accurate production predictions. A comprehensive simulation is conducted, comparing scenarios with solar batteries, without solar batteries, and without a photovoltaic installation to analyze the results.

Cost reductions were made possible by the use of second-life batteries, due to their significantly lower price, and the strategic management of electricity tariffs, which allowed grid usage during economically beneficial hours.

Keywords: Photovoltaic Panels, Second Life Batteries, Electricity Tarrifs, Monitoring System, SHEMS, Artificial Intelligence

RESUMO

Caminhamos para um mundo cada vez mais autónomo e procuramos sempre tirar o maior proveito das tecnologias desenvolvidas como é o caso das instalações fotovoltaicas em habitações onde a maior parte das pessoas procura aproveitar a energia do sol para alimentarem as suas habitações ou veículos ou até mesmo na criação de comunidades elétricas para um maior rendimento energético e ajuda na "descarbonização".

O problema surge quando não há energia solar disponível mas há uma necessidade de consumo, ou seja, quando não há sol não há energia, numa perspetiva autónoma. Uma bateria solar parece ser a solução mais óbvia mas traz também problemas associados como um grande investimento tornando este problema dos painéis fotovoltaicos desafiante.

Surge então a necessidade de arranjar soluções, solução essa que pretendo desenvolver nesta tese que consiste em desenvolver um sistema capaz de controlar uma instalação fotovoltaica com bateria solar e adotar métodos para compensar o investimento inicial. Métodos estes como o controlo das tarifas energéticas e uso de baterias usadas, "Second Life Batteries", baterias usadas em carros elétricos que não são consideradas ideais para manter o desempenho do carro devido ao "estado de vida"chegar abaixo dos 80%.

Esta tese delineia o desenvolvimento de um sistema inteligente, ***WattFuture***, projetado para supervisionar uma instalação fotovoltaica doméstica que incorpora baterias solares. Para alcançar esse objetivo, serão implementados modelos de Inteligência Artificial para prever valores energéticos, sendo estes produção e consumo. A integração de application programming interfaces, APIs, fornece informações meteorológicas necessárias para previsões da produção mais precisas. Realizou-se uma simulação abrangente, contrastando cenários com baterias solares, sem baterias solares e sem instalação fotovoltaica para comparar resultados.

As reduções de custos foram possíveis graças à utilização de baterias usadas, devido ao seu preço significativamente mais baixo, e à gestão estratégica das tarifas de eletricidade, que permitiu a utilização da rede em horas economicamente vantajosas.

Palavras-chave: Painéis Fotovoltaicos, Baterias Usadas, Tarifas energéticas, Sistema de Monitorização, SHEMS, Inteligência Artificial

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ACRONYMS

AC	Alternating Current *(pp. 52, 53)*
AI	Artificial Intelligence *(pp. 7, 8)*
AIMMS	Advanced Interactive Multidimensional Modelling System *(p. 17)*
ANN	Artificial Neural Networks *(pp. 7, 8, 48, 98)*
API	Application Programming Interface *(pp. 28, 31, 34, 44, 52, 56)*
ARIMA	AutoRegressive Integrated Moving Average *(pp. 7, 8)*
CAISO	California Independent System Operator *(p. 12)*
CBR	Case-Based Reasoning *(pp. 23, 24)*
CLI	Command Line Interface *(p. 56)*
CORS	Cross-Origin Resource Sharing *(p. 56)*
DC	Direct Current *(p. 52)*
DoD	Depth of Discharge *(p. 14)*
DSM	Demand Side Management *(pp. 5, 26)*
EIA	Energy Information Administration *(p. 10)*
EMS	Energy Management Strategies *(p. 1)*
EOL	End of Life *(p. 14)*
ERSE	Regulatory Entity of Energy Services *(pp. 18, 19)*
ESS	Energy Storage System *(p. 12)*
EV	Electric Vehicle *(pp. 14, 15, 22, 27, 67)*
EVB	Electric Vehicle Batteries *(p. 15)*
FiT	Feed-in Tariff *(p. 17)*
FLC	Fuzzy Logic Controller *(p. 25)*
HEMS	Home Energy Management Systems *(p. 5)*
HTTP	Hypertext Transfer Protocol *(pp. 44, 56)*

ICT	Information and Communication Technology *(p. 6)*
K-NN	K-Nearest Neighbors Algorithm *(pp. 48, 49)*
KWh	Kilo Watt hour *(pp. 18, 20)*
LIB	Lithium-ion Battery *(pp. 1, 15, 27)*
MAE	Mean Absolute Error *(p. 50)*
MPPT	Maximum Power Point Tracking *(p. 67)*
MSE	Mean Squared Error *(pp. 49, 50)*
MVC	Model-View-Controller *(p. 56)*
NOCT	Nominal Operating Cell Temperature *(p. 52)*
ORM	Object Relational Mapping *(pp. 38, 56)*
PHP	Hypertext Preprocessor *(p. 55)*
PuLP	Python Linear Programming *(pp. 38, 53–55)*
PV	Photovoltaic *(pp. 1, 2, 10–14, 17, 18, 26–28, 30–33, 35, 37, 39–41, 43, 44, 52–55, 64–69, 71, 73, 75, 77, 79, 81, 83, 85, 87, 89, 91, 93, 97)*
RBS	Rule-Based System *(pp. 23, 24)*
RMSE	Root Mean Squared Error *(p. 50)*
ROI	Return of Investment *(p. 98)*
SHEMS	Smart Home Energy Management Systems *(pp. 6, 8, 9)*
SLB	Second Life Batteries *(pp. 1, 2, 14, 15, 27, 67, 68)*
SLR	Supplier of Last Resort *(p. 18)*
SoC	State-of-Charge *(pp. 25, 27, 53, 64, 67)*
SoH	State of Health *(pp. 13, 14, 24, 27, 64, 67, 85)*
STC	Standard Test Conditions *(p. 52)*
URL	Uniform Resource Locator *(p. 56)*
WF	WattFuture *(pp. 66, 68, 69, 71, 73, 77, 79, 81, 85, 87, 89, 95–97)*

1

INTRODUCTION

1.1 Motivation & Problem

It is widely recognized that the trajectory of energy production is leaning towards renewable sources, with the generation of electricity using photovoltaic panels emerging as a particularly popular option, as mentioned by Inês Santos (2023). An article from "Trends in PV Applications 2023" (2023) shows that 6,2% of the world's electricity was generated by photovoltaic panels in 2022. This achievement was made possible by the 65% increase in Photovoltaic (PV) installations over the past 5 years, making solar one of the fastest growing energy sources. However, the article from "Trends in PV Applications 2023" (2023) also highlights that challenges remain as this solution is not able to produce during periods without sunlight.

If this is the future, we must focus on making the most of it, and one possible solution relies on batteries. It's known that they can be expensive, but there's no need to invest in new batteries when we can help the environment and save money by choosing Second Life Batteries (SLB). According to Kamath et al. (2020), a significant portion of automotive lithium-ion batteries, commonly referred to as Lithium-ion Battery (LIB)s, undergo recycling processes. However, there is potential for these batteries to be repurposed as second-life batteries since they often retain 70-80% residual capacity, making them suitable for stationary applications. The author, Kamath et al. (2020), also highlights that SLBs have been proposed as cost-effective, environmentally friendly energy storage solutions for both residential and utility-level applications, whether integrated with PV panels or not. The study from Kamath et al. (2020) also shows that utilizing SLBs has demonstrated a reduction in the levelized cost of electricity by 12-57% and a decrease in carbon emissions by 7-31%.

Despite these advantages, the adoption of SLB's is not enough to ensure cost efficiency and optimal energy use. The way in which these energy storage systems are managed plays a crucial role in determining their economic and environmental impact. Energy Management Strategies (EMS) are employed to strategically plan the operation of various equipment within a microgrid, including loads, storage, or electrical production means.

The primary goal is to minimize operating costs, optimize energy utilization, and, in some cases, mitigate environmental impacts, as mentioned by Ouédraogo et al. (2022)

Looking ahead, the future of energy is seen as a world characterized by autonomy and near complete individual independence from conventional energy sources. However, to achieve this, it is crucial to develop innovative strategies that enhance the efficiency of SLB's and leverage electricity pricing mechanisms to maximize savings. By intelligently managing when and how batteries are charged and discharged, based on solar generation patterns, energy demand, and dynamic electricity tariffs, it is possible to achieve significant cost reductions while maintaining energy reliability.

In pursuit of this futuristic ideal, this work aims to explore innovative pathways and potential optimizations to unlock the full potential of SLB's and PV systems that ensure a sustainable, cost-effective, and resilient energy future.

1.2 Objectives And Expected Contributions

In order to address the previously stated problems, this dissertation will explore diverse methodologies and strategies. The main concern with solar batteries lies in their substantial cost. However, studies from Colarullo and Thakur (2022) or Kamath et al. (2020), for example, suggest that new batteries may not always be necessary as SLBs have been proven to be able to support photovoltaic systems with a much lower cost. The incorporation of Second Life Batteries, repurposed batteries from electric vehicles with a State of Health below 80% presents a viable alternative for integration into photovoltaic systems. Notably, these batteries can be acquired at a lower price, around 1/3 of the initial price.

Turning attention to the aspect of limited lifespan, the assumption that used batteries inherently possess a diminished lifespan is challenged. Battery degradation follows a non-linear trajectory, with faster deterioration observed from 100% to 80% than from 80% to 60% as mentioned in Mathews et al. (2020). A detailed discussion on this phenomenon will be presented later in the dissertation.

While these concepts are not groundbreaking, the primary objective is to develop a system model for effective control and utilization of these batteries, particularly in alignment with electricity tariffs. In detail, the proposed system model takes a proactive stance in predicting user consumption patterns and energy requirements. By employing advanced analytics, the model systematically analyzes the optimal approach to fulfill these needs. This includes discerning opportune moments to harness low peak tariffs or leverage high solar radiation, ensuring a judicious balance between cost savings and operational efficiency. The overarching goal of the system model is to guarantee unparalleled energy optimization, fostering both economic savings and enhanced user comfort.

This dissertation is built upon the work presented by Santos, 2023. Her work primarily focuses on optimizing solar energy utilization through a monitoring system designed to manage household appliances in real-time. It is noteworthy that she chose not to incorporate batteries as that was not her goal. Furthermore, her research does not encompass topics such as tariffs or energy communities, which can be key considerations for optimizing a solar system if the results prove it. In conclusion, the main contributions of this dissertation are:

1. **Optimization of a battery to increase its lifespan** - Employing the monitoring system to determine the optimal utilization of energy resources, such as deciding whether to draw power from the battery or the grid, and identifying the most favorable moments for battery charging.
2. **Enhanced energy flexibility ensures a reliable supply of energy precisely when required** - The system's predictive capabilities allow it to anticipate customer demands, guaranteeing a consistent and readily available energy supply to meet those needs.
3. **Development of a model aimed at optimizing the advantages offered by electricity tariffs** - The system intelligently avoids unnecessary expenses during high peak tariffs by strategically charging the battery during periods of lower tariff rates, resulting in substantial cost savings.
4. **Enhancing energy management through communities** - The system is designed to allow the integration of two or more households into an energy community, enabling more uniform energy loads. This uniformity facilitates the model's ability to effectively evaluate and optimize the selection of energy sources. Although the system is prepared for energy communities, it has not been possible to implement it in practice.

1.3 Document Organization

This thesis is divided in 6 sections:

1. **Introduction** - This section introduces the motivation behind this work and outlines the main objectives and contributions.
2. **Background** - This section provides an overview of the key technologies, methodologies, and techniques relevant to energy management systems, with a focus on enhancing system efficiency and addressing current challenges.
3. **Conceptual Approach** - This section outlines the theoretical framework and strategies adopted to design the energy management system, including the integration of predictive models and the use of community-based energy optimization.
4. **System Implementation** - This section details the practical development of the system, including the technologies used, system architecture, and the integration of APIs, machine learning models, and simulation tools.

5. **Results** - This section presents the outcomes of the system's simulations and predictions, comparing various scenarios to demonstrate the effectiveness of the proposed solution in improving energy management.
6. **Conclusion** - This section offers a concise summary of the thesis objectives, the key findings, and the benefits derived from the proposed solution, while also suggesting directions for future improvements.

2

Background

2.1 Smart Homes

A smart home integrates connected technologies to monitor and control appliances, lighting, and energy systems remotely or automatically.

A continuous monitoring system is essential for smart home energy management. By analyzing both production and consumption in real time, it becomes possible to optimize usage and make informed decisions about what is most beneficial, improving return on investment.

The Home Energy Management Systems (HEMS) is crucial in the Demand Side Management (DSM) of the residential sector, aiming to enhance the energy efficiency of households through intelligent control of various smart home entities, as highlighted by Yao et al. (2017) and many others.

2.1.1 Benefits of a Smart Home

These types of systems bring various benefits, such as:

1. **Energy Efficiency** - Smart homes can significantly improve energy efficiency by automating the control of heating, lighting, ventilation, dishwasher and other appliances. This can result in lower energy consumption and reduced utility bills.

2. **Convenience** - Automation allows for remote control and monitoring of various devices, making daily tasks more convenient. This includes adjusting thermostat settings, turning off lights, or even managing home security systems from a smartphone.

3. **Enhanced Security** - Smart home security systems provide real-time monitoring and alerts, helping homeowners keep their property safe. Surveillance cameras, smart doorbells, and motion sensors can contribute to a more secure living environment.

4. **Improved Comfort** - Autonomous systems can learn user preferences and adjust settings accordingly, providing a personalized and comfortable living space. For example, smart thermostats can adapt to occupants' schedules and preferences.

2.1.2 Challenges of a Smart Home

On the other hand, according to Sharma (2019) there are some challenges to be overcome:

1. **Cost** - The initial setup cost of smart home devices and systems can be relatively high. This may act as a barrier for some users, although the prices have been decreasing as the technology becomes more widespread.

2. **Interoperability Issues** - Different smart devices may use different communication protocols, leading to interoperability challenges. Ensuring seamless integration between devices from various manufacturers can be complex. Elkhodr et al. (2016)

3. **Privacy and Security Concerns** - With the increasing connectivity of devices, there are heightened concerns about the privacy and security of personal data. Vulnerabilities in smart home systems could potentially be exploited by malicious actors. Elkhodr et al. (2016)

2.1.3 Smart Home Energy Management Systems

In recent times, Smart Home Energy Management Systems (SHEMS) have experienced rapid development. Advanced techniques empower SHEMS to facilitate network control through demand responses, potentially involving peak consumption reduction, load shifting, and ancillary services, as discussed by Liu et al. (2016).

Although SHEMS has been a presence in the energy sector for several decades, its primary functions involve monitoring, controlling, and optimizing the flow and utilization of energy, as noted by Asare-Bediako et al. (2012).

This innovative system is designed to enhance energy efficiency and user control within a smart home environment. According to Liu et al. (2016), SHEMS is divided in five parts:

1. **Measuring Device** - Measuring devices are fundamental to SHEMS. Measuring electricity, gas and water is the key to control it.

2. **Sensing Device** - For more accurate measurements, sensors such as those for current detection and voltage are indispensable. These sensors enable the monitoring and control of smart appliances.

3. **Information and Communication Technology (ICT)** - ICTs are essential for linking sensors to the controller. ICT is the linking pin connecting the sensor, meters and devices to the monitoring or control unit. Both wireless and wired options, have

been developed to facilitate the integration of diverse domestic devices. Cardova et al. (2011)

4. **Smart Appliances** -Smart appliances play a crucial role in offering residential customers insights into their energy consumption patterns. This understanding empowers users to adopt more energy-efficient and eco-friendly behaviors, as emphasized in Liu et al. (2016) Equipped with integrated intelligence and communication systems, smart appliances empower the controller to exert remote monitoring and control over their functionalities.

5. **Energy Management System** - This component involves the development of user-friendly software. It furnishes users with detailed energy data, enables programming of preferences and priorities, and facilitates forecasting and scheduling of loads, enhancing overall energy management capabilities.

2.1.4 Artificial Intelligence

Artificial Intelligence (AI) and predictive models play a key role in the evolution of smart home energy management systems, revolutionizing the way we optimize energy consumption and enhance overall efficiency. In the context of a smart home energy management system, the integration of AI technologies introduces a layer of intelligence that goes beyond conventional programming, enabling systems to adapt, learn, and make informed decisions based on real-time data.

Predictive models, a subset of AI applications, hold immense potential in forecasting energy consumption patterns, thereby contributing significantly to the optimization of resources. These models analyze historical data, user behavior, and external factors to anticipate future energy demands, enabling proactive measures for efficient energy utilization.

Sources like da Conceição (2021) and Rocha et al. (2021) already have study some techniques and predictive models in energy management systems, such as Artificial Neural Networks (ANN), Metaheuristic Algorithms, AutoRegressive Integrated Moving Average (ARIMA) among others.

Conceição's study shows that a box-jenkins method, using ARIMA model, is proven to be very accurate when predicting temperature and irradiance values. This model showed a mean absolute error of 3.32% and a root mean square error of 0.59% within 48 hours for temperature predictions and an average absolute error of 1.79% within 24 hours for irradiance predictions.

However, this model may not be the best option for consumption predictions since consumption values differ from every scenario and so, it requires a more adaptable approach. This is where ANN emerge as a valuable tool for consumption predictions in smart home energy management systems.

Artificial Neural Networks are computer models inspired by the neural structure of the human brain. They consist of interconnected nodes, or artificial neurons, organized in layers. In the context of energy consumption predictions, ANN excel at capturing complex patterns and relations within data. Unlike traditional models like ARIMA, ANN can adapt to varying input features and learn from diverse datasets. Yin et al. (2024) Furthermore, Alayed et al. (2025) article demonstrates the ability of ANN's to predict energy consumptions.

In conclusion, while models like ARIMA demonstrate accuracy in certain aspects of energy prediction, such as generation, Artificial Neural Networks stand out for their versatility and capacity to handle the intricacies of consumption forecasting in dynamic and diverse smart home environments. As the field of AI continues to progress, integrating sophisticated predictive models will be crucial for unlocking the full potential of smart home energy management systems.

2.1.5 Architecture of a Smart Home

For a better understanding of the SHEMS concept, let's explore its architecture as depicted in Figure 2.1. The SHEMS Center plays a crucial role in monitoring, managing, and controlling the system. This is accomplished through a microcontroller, like an Arduino, on the consumer's side, connected to different components such as web servers, sensors, actuators, etc.

The cloud/web server monitor the energy management system, it is used for large data store and analysis. In fact, the cloud/web server parses data and acts accordingly to save energy, and it can also generate statistical information and plotting graph to help users act and avoid electricity waste, Chouaib et al. (2019). This data empowers the SHEMS Center to make informed decisions, such as choosing between energy sources, either from the grid or the energy storage system. Additionally, it enables the optimization of load distribution by shifting loads strategically. The system can also capitalize on low-peak intervals to charge the battery efficiently, subsequently discharging it during periods of higher electricity prices.

Additionally, an optimized energy management scheme can further enhance cost minimization and user comfort by scheduling home appliances based on load type, prioritizing self-generated PV power, and dynamically dispatching electricity from the grid, as proposed by Yao et al. (2017).

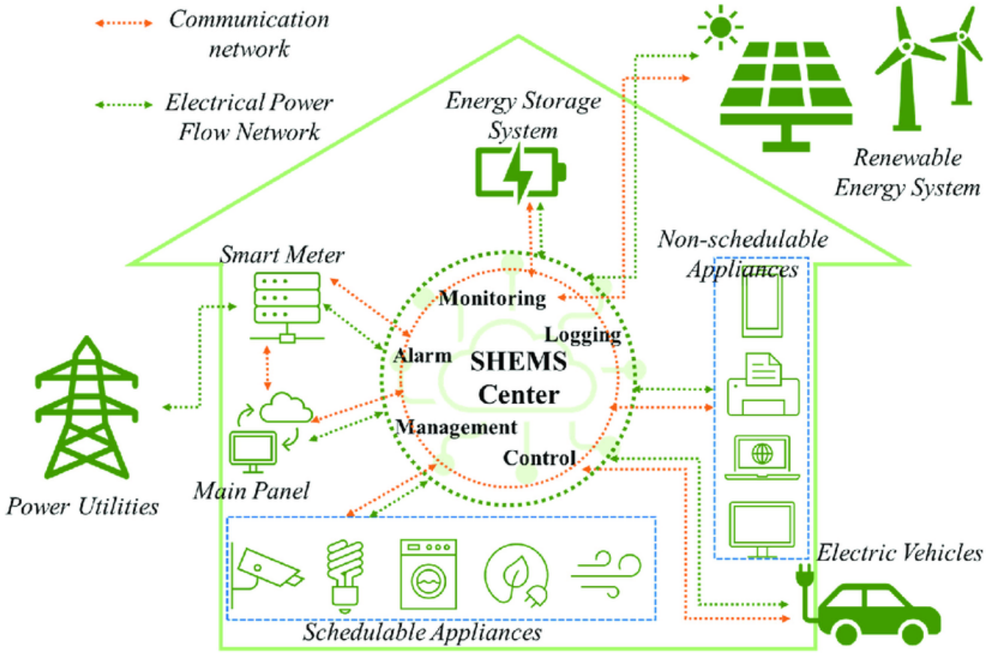


Figure 2.1: The overall architecture of a representative Smart Home Energy Management Systems, SHEMS, Elkholy et al. (2022)

This system operates autonomously but it can offer users control through a dedicated application. This feature enhances user comfort and contributes to an elevated quality of life.

2.1.6 Types of Appliances

Regarding the energy aspect of smart appliances, these devices possess the capability to receive, interpret, and act on signals received from an energy provider. They can adjust their operation according to the settings chosen by the energy consumer, as explained by Serrenho and Bertoldi (2019).

As previously mentioned, SHEMS will help managing and controlling appliances in order to provide the best quality in terms of efficiency and life comfort but we need to define types of appliances because they are not all the same and can't be treated equally.

An article from Rahim et al. (2016) organized the appliances in three categories based on the priority of usage of each device and customized accordingly to the preferences of each user. These categories are elastic appliances, shiftable appliances, and fixed appliances as illustrated in Table 2.1. Elastic appliances are defined as being fully controllable when it comes to both usage time and power consumption. On the other hand, shiftable appliances can be shifted in time without needing to alter the load profile and are characterized by their operation time, pre-defined by the user. Lastly, a fixed appliance's usage or power consumption cannot be altered, therefore it has fixed values.

Table 2.1: Types of Appliances from Elkholy et al. (2022)

Appliance	Type of Appliance	Pre-Defined Schedule of Operation		
		Inside	Away	Sleep
Water Pump	Elastic Appliance / Schedulable	On Request	Off	Off
Refrigerator		On	On	On
Air Conditioner		On Request	Off	On Request
Vacuum Cleaner		On Request	Off	Off
Water Heater		On Request	Off	Off
Space Heater		On Request	Off	Off
Washing Machine	Shiftable Appliance / Schedulable	On Request	On Request	Off
Cloth Dryer		On Request	On Request	Off
Dish Washer		On Request	Off	Off
Fan	Fixed Appliances / Non-schedulable	On Request	Off	On Request
TV		On Request	Off	Off
Light		On Request	Off	Off
Microwave		On Request	Off	Off

2.2 Photovoltaic Panels

The adoption of Photovoltaic (PV) Panel installations has witnessed remarkable growth year after year, showing no signs of slowing down. In 2023, approximately 447 gigawatts of new PV capacity were installed worldwide, bringing the total global solar capacity to about 1.6 terawatts. Meban (2023) This increase in PV installations emphasises the key role of solar energy in the transition to sustainable and renewable power sources. Photovoltaic panels have emerged as the leading renewable energy technology, contributing significantly to the global effort to reduce carbon emissions and combat climate change.

Global energy consumption has exhibited consistent growth over the past few decades, leading to a significant increase in world energy demand. Simultaneously, the depletion of fossil fuel resources and the associated pollution from their consumption pose significant challenges.

Addressing these issues necessitates a thoughtful approach, and renewable energies emerge as a promising solution, as noted by Mehrtash et al. (2012).

Renewable energy sources encompass various options such as solar, wind, hydro, geothermal, biomass energies, among others. Among these, solar energy stands out as a crucial renewable resource that has been harnessed for electricity generation for many years, as highlighted in Jayakumar (2009).

Energy Information Administration (EIA) projects that renewable generation will supply 44% of U.S. electricity by 2050 as mentioned in Administration (2022). Figure 2.2 illustrates that within those 44%, more than half will be from solar energy.

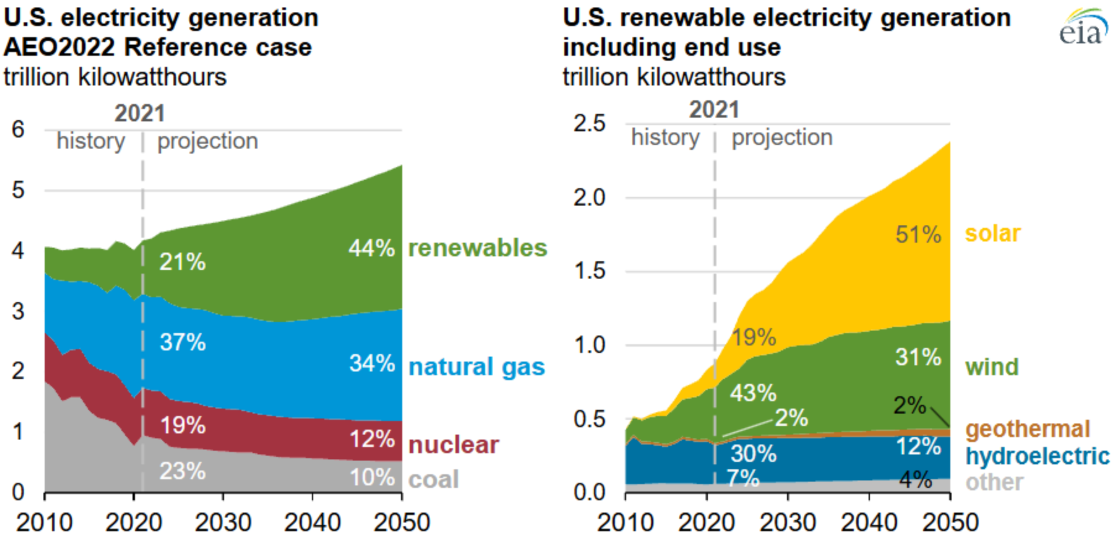


Figure 2.2: Renewable Energy Generation Projections, according to U.S. Energy Information Administration from Administration (2022)

2.2.1 Importance of PV Panels

Enel (2021), published in Enel's website, provides several benefits of solar energy, such as:

1. **Environmental Sustainability** - PV panels generate clean energy without emitting greenhouse gases, therefore reducing the carbon footprint associated with electricity consumption.
2. **Economic Advantages** - Advancements in PV technology have led to significant cost reductions, making solar energy increasingly competitive with traditional energy sources. Investments in solar installations can result in long-term savings on energy bills and provide a hedge against fluctuating fossil fuel prices.
3. **Energy Independence** - Utilizing solar energy can reduce dependence on imported fuels, enhancing energy security for both individuals and nations.
4. **Job Creation** - The solar industry has become a significant source of employment, offering jobs in manufacturing, installation, maintenance, and research and development

These advantages of solar energy led to an obvious increase of solar energy generation. However, it is important to understand their limitations and challenges that might impact this work.

2.2.2 Challenges

Well, even thought this technology is great, there are some challenges and factors that affect its performance. Environmental factors, PV system factors, installation factors, cost factors or miscellaneous factors are the main factors that were studied by Fouad et al. (2017).

Environmental factors encompass solar irradiance, temperature, and shading, with solar irradiance being directly correlated with energy production. In instances of insufficient radiation, production experiences adverse effects. PV cells can only convert less than 20% of irradiance into electrical energy, with the remaining being transformed into heat. Elevated PV temperatures contribute to decreased performance. Lastly, partial shadowing occurs when surrounding objects cast shadows on specific sections of a photovoltaic (PV) array, leading to non-uniform irradiance reaching the PV modules. This non-uniform shading induces an electrical mismatch among the array components, causing a non-linear loss in energy collection, as highlighted in Iysaouy et al. (2023).

PV system factors are associated with the components of the PV system and can significantly impact overall efficiency. Parameters such as the I-V curve, inverter efficiency, PV structure, and PV materials influence overall performance and warrant thorough consideration in simulations.

Installation factors, including cable characteristics, angle and orientation of PV panels, fixed mechanisms, and mismatch effects, can impact the installation process. Poor-quality cables may result in energy losses, suboptimal angles or orientations can diminish potential energy production, fixed mechanisms may fail to efficiently track solar radiation, and connecting non-matching solar modules can negatively affect system production.

Cost factors influence performance, with high-quality systems offering minimal losses but requiring a higher initial investment.

Lastly, miscellaneous factors such as PV panel degradation over time, structural damage, hotspots, shunt resistance, and performance ratios will be meticulously considered in the ensuing simulation.

2.2.3 Duck Curve Effect

The increase of photovoltaic systems in households and buildings started to have some impact on the grid. This was noticed back in 2012 in California.

As described in Calero et al. (2022), the solar power duck curve characterizes a distinctive demand pattern observed by the California Independent System Operator (CAISO) resulting from the widespread integration of solar PV resources into the grid as seen in figure 2.3. On certain days, the net demand displays a notable dip in the mid-afternoon, resembling a belly, followed by a rapid ascent, forming an arch or neck in the evening.

The typical solutions to address this issue involve strategies to flatten the demand curve, such as the judicious use of Energy Storage System (ESS), incorporating more flexible resources, and promoting the electrification of transportation, among other measures, as outlined in Calero et al. (2022)

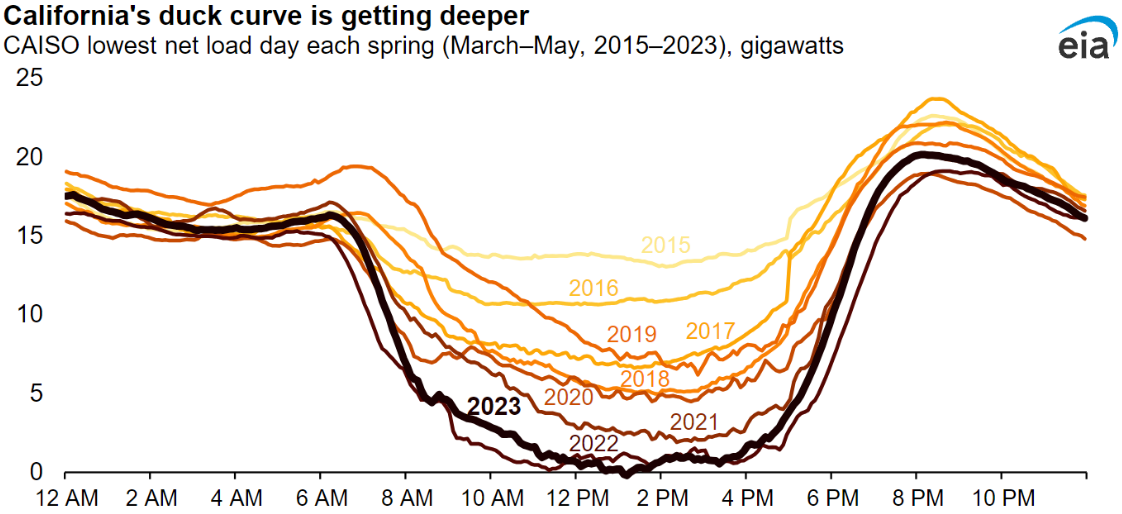


Figure 2.3: Solar Power Duck Curve from California Independent System Operator, CAISO

With this in mind, this work will also help combat the duck curve problem with a monitoring system using batteries, as there won't be a need for such abrupt increases and decreases in grid consumption.

2.3 Batteries

As previously discussed, the integration of batteries into PV systems significantly enhances their overall quality and flexibility. These batteries effectively address challenges posed by PV panels, as they can store energy to use during periods of insufficient solar irradiance, thereby enhancing system flexibility. It is crucial to note, however, that this approach is not without its imperfections, as considerations such as cost, lifespan, and safety aspects remain pertinent.

2.3.1 Batteries Degradation

To ensure this work yields the most precise results, it is important to account for battery degradation.

Improving the accuracy and robustness of State of Health (SoH) estimation is a viable strategy for enhancing the performance and economics of battery systems in photovoltaic PV systems. However, measuring SoH directly is not feasible, and its estimation is a challenging task due to various influencing factors, as highlighted in Tian et al. (2019).

Several factors contribute to this phenomenon, including the repetitive charge and discharge cycles of batteries, a concern particularly pronounced in (PV) systems due to the absence of a standardized loading profile. Conversely, PV systems often involve lower currents, which generally extends the life expectancy of batteries.

Numerous estimation methods are available for evaluating battery state as mentioned in the following section 2.6.2 of this dissertation.

2.3.2 Second Life Batteries

The swift expansion of electric vehicles is generating a substantial fleet of lithium-ion batteries, which will be considered unsuitable for the transportation industry once they reach 80% of their original capacity, as outlined by Mathews et al. (2020).

This millions of lithium-ion batteries will ultimately find their fate in a landfill, undergo recycling, or be repurposed for a second life application. The first option, while cost-effective, comes with significant environmental consequences. The second option is more environment friendly but it requires patented process and requires strong expertise in the chemical and metallurgical fields, says Mathews et al. (2020). Laslty, there is an option to repurpose these batteries for use in a second life application, such as integrating them into a domestic photovoltaic system. Although a battery End of Life (EOL) is usually set to be SoH=80% for Electric Vehicle (EV) batteries, mentioned by Yang et al. (2018), it can be lower for PV systems due to their low power and capacity requirements.

For example, the study from Mathews et al. (2020) shows that after 10 years of operation, the new battery has faded from 100% to 75% useful capacity, a loss of 25%, while the second-life battery has faded from 80% to 63%(when limited between 20% and 85%), a loss of 17%.

One interesting observation is that battery degradation is not linear. With proper use(15-65% range), a Second Life Batteries (SLB) with 80% SoH can last almost as long as a new battery as can be seen in figure 2.4. Figure 2.4 is the aging of remaining useful capacity with time for second-life and new batteries, for different Depth of Discharge (DoD) usage ranges. The graph is a comparison of four usage profiles:

1. 95-15% (green line)
2. 65-15% (purple line)
3. 85-20% (blue line)
4. New battery cycling from full charge (dark blue line)

The data shows that narrower and lower usage ranges, namely 65-15%, decelerate the degradation rate to a large extent. For instance, an SLB, operated at such a range, retains usable capacity for a longer period of time, approaching the fresh battery performance curve. This shows the non-linear nature of battery degradation and explains the methodology adopted in this dissertation, in which the system is made to operate in a 65-15% range to achieve the maximum life of the battery.

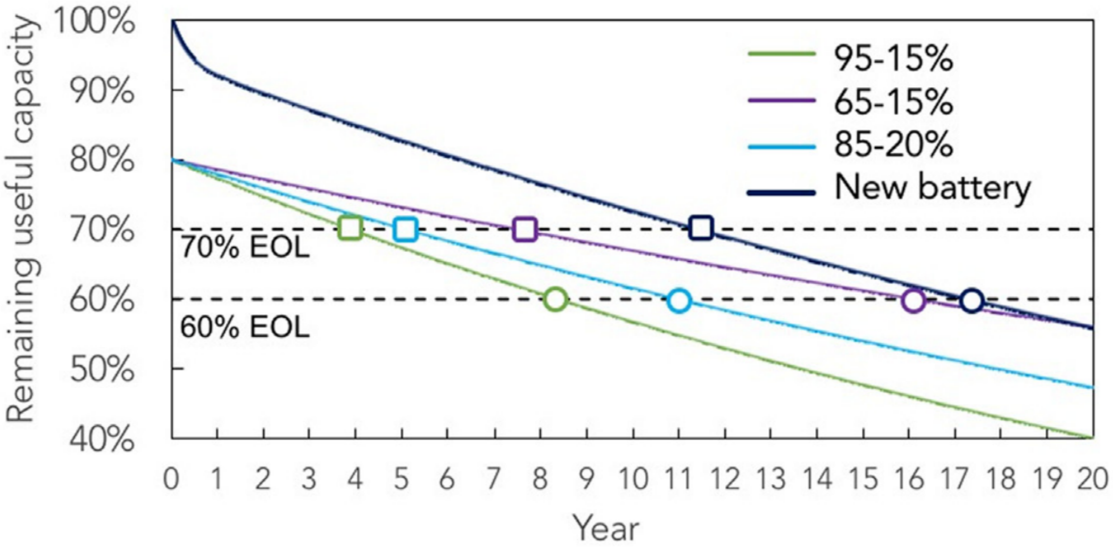


Figure 2.4: State of Health, SoH, over time from Mathews et al. (2020)

Repurposing these used batteries offers a significant opportunity for new applications with less demanding duty cycling and current levels compared to EV driving. This approach can potentially provide a low-cost source of lithium-ion batteries for new applications, thereby increasing a battery's lifetime value and delaying the eventual cost of recycling, as discussed by Harper et al. (2019). As mentioned in Colarullo and Thakur (2022), this SLB can be used for load shifting, meaning pre-charging during low price periods and discharging during high price periods.

2.3.3 Batteries Costs

It is challenging to assign a specific value to batteries due to their continuous evolution. With the exponential rise of electric vehicles each year, it is anticipated that the costs of used batteries will further decrease.

According to Dong et al. (2023) the cost of second-life Electric Vehicle Batteries (EVB) falls within the range of 20%-80% of new batteries.

Figure 2.2 provides a perspective on possible Lithium-ion Battery (LIB) prices, and some studies indicate that retired batteries can be as low as 1/3 of the initial price. According to Liu's study Jian (2017), the price of second-life EVB for energy storage was 72$/kWh, and the price of a new EVB was $232/kWh. Another article Sun et al. (2020) estimated that in China, the price of retired EVB was about $23-31/kWh, and the selling price was about $62-70/kWh after testing, screening, and recombination.

2.4 Electricity Tariffs

In modern days each person has their routine, managing their consumptions in unique ways. Despite these differences, a commonality among the majority is their engagement

Table 2.2: Lithium-ion Battery, LIB, cost estimates from Dong et al. (2023)

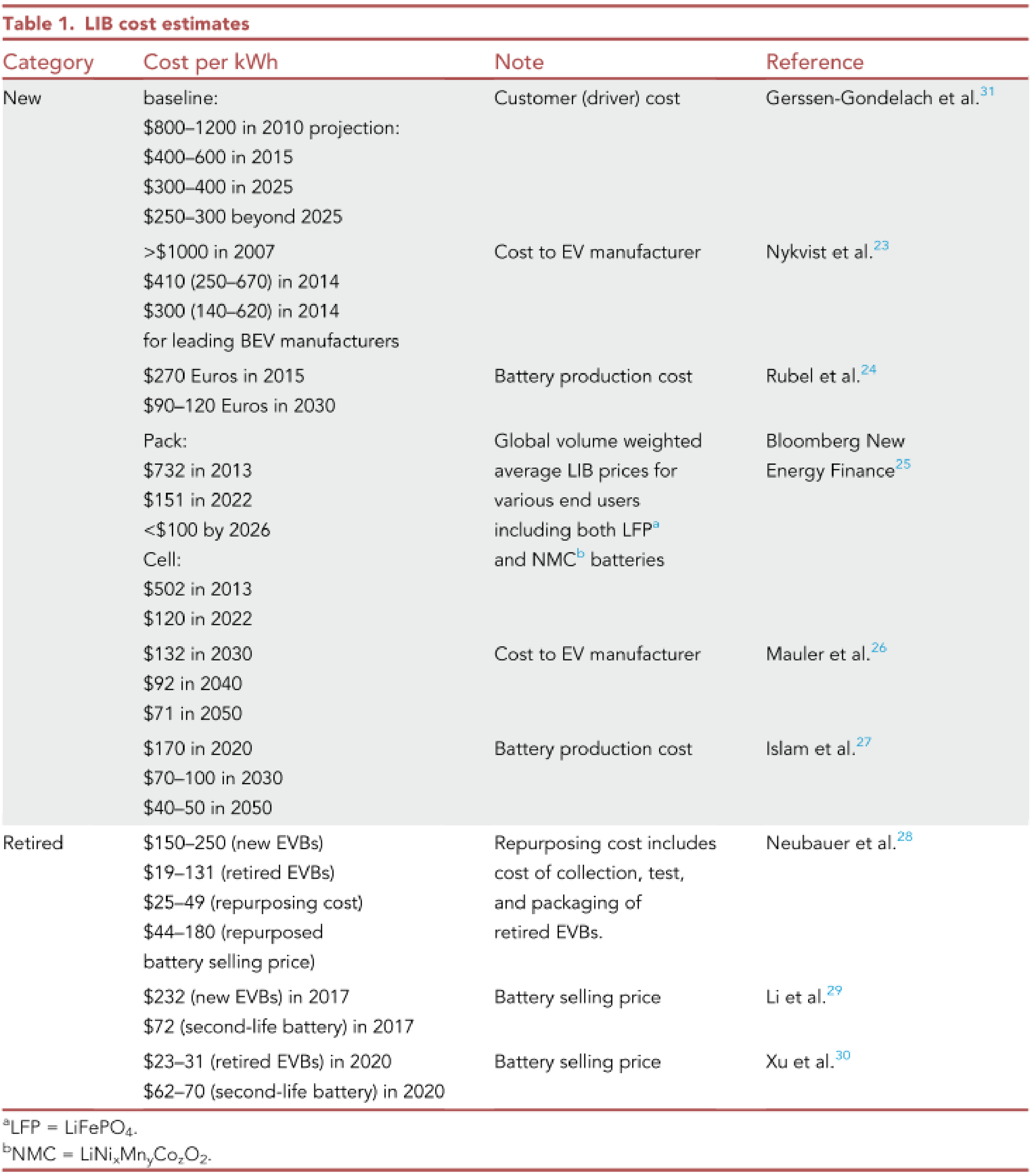


Table 1. LIB cost estimates

Category	Cost per kWh	Note	Reference
New	baseline: \$800–1200 in 2010 projection: \$400–600 in 2015 \$300–400 in 2025 \$250–300 beyond 2025	Customer (driver) cost	Gerssen-Gondelach et al.[31]
	>\$1000 in 2007 \$410 (250–670) in 2014 \$300 (140–620) in 2014 for leading BEV manufacturers	Cost to EV manufacturer	Nykvist et al.[23]
	\$270 Euros in 2015 \$90–120 Euros in 2030	Battery production cost	Rubel et al.[24]
	Pack: \$732 in 2013 \$151 in 2022 <\$100 by 2026 Cell: \$502 in 2013 \$120 in 2022	Global volume weighted average LIB prices for various end users including both LFP[a] and NMC[b] batteries	Bloomberg New Energy Finance[25]
	\$132 in 2030 \$92 in 2040 \$71 in 2050	Cost to EV manufacturer	Mauler et al.[26]
	\$170 in 2020 \$70–100 in 2030 \$40–50 in 2050	Battery production cost	Islam et al.[27]
Retired	\$150–250 (new EVBs) \$19–131 (retired EVBs) \$25–49 (repurposing cost) \$44–180 (repurposed battery selling price)	Repurposing cost includes cost of collection, test, and packaging of retired EVBs.	Neubauer et al.[28]
	\$232 (new EVBs) in 2017 \$72 (second-life battery) in 2017	Battery selling price	Li et al.[29]
	\$23–31 (retired EVBs) in 2020 \$62–70 (second-life battery) in 2020	Battery selling price	Xu et al.[30]

[a] LFP = $LiFePO_4$.

[b] NMC = $LiNi_xMn_yCo_zO_2$.

in full-time jobs or school, leading to a significant amount of time spent away from home, typically within the same time frame, 9 am to 5 pm.

However, the COVID-19 pandemic changed the usual household energy consumption pattern, not only during but after the pandemic. A study from Khalil and Fatmi (2022) observed notable changes, with a 29% rise in residential energy consumption during the pandemic, and an expected 12% increase pos-pandemic.

Another study, from Ferrando et al. (2023) confirms this energy consumption pattern changes and it shows several different behaviors.

Despite the pattern differences, it is possible to create a graph with the average consumption behavior as shown in figure 2.5. Here, we observe that the average electricity consumption is not well-balanced. As highlighted by Ulbig et al. (2014), demand and supply should be balanced all the time in electric grids.

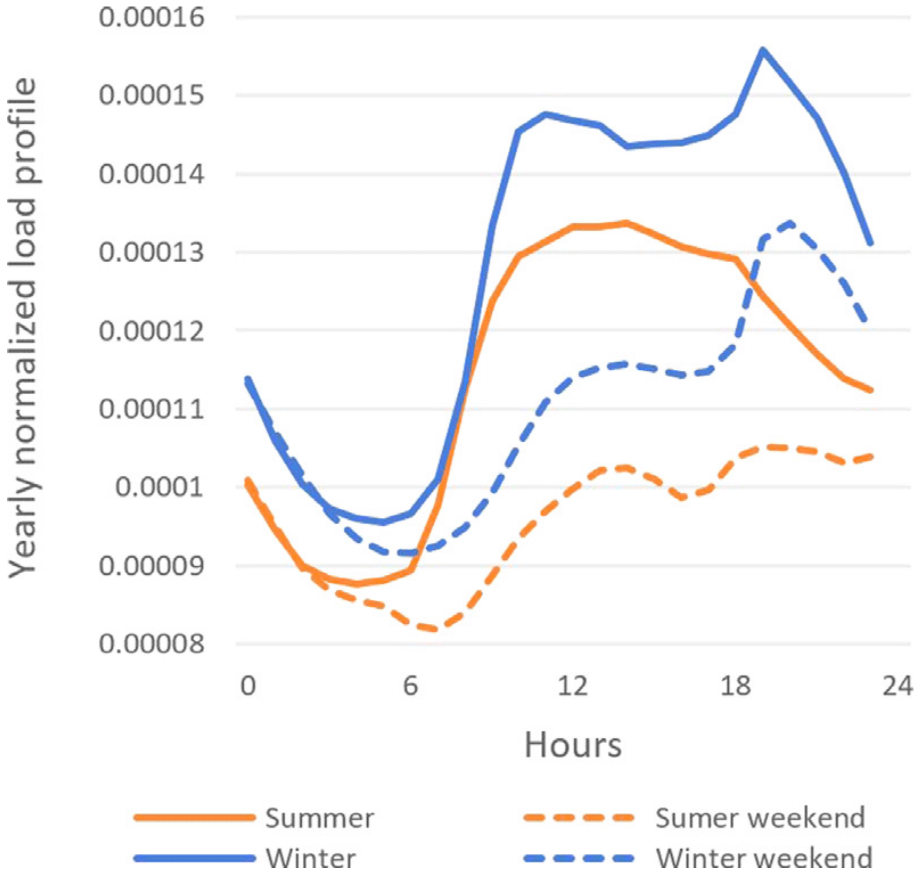


Figure 2.5: Average electricity consumption in Netherlands from Fattahi et al. (2021)

Another interesting article is Hassan et al. (2017). This article shows a study made to optimize battery storage in a PV system using tariff incentives. The author used an optimization model for maximizing Feed-in Tariff (FiT) revenue from Advanced Interactive Multidimensional Modelling System (AIMMS). It was then created a modified function to include tariff and wholesale tariff to compute the net revenue from onsite generation and the export of electricity.

Three tests have been studied:

- **Case study 1** - PV under FiT with no battery storage and buying electricity from the grid with flat electricity tariff.
- **Case study 2** - PV with battery storage under FiT and economy tariffs.
- **Case study 3** - PV with battery storage under FiT tariff and considering wholesale tariff as electricity import tariff.

As expected, case study 1 shows high grid dependence due to low solar irradiance during winter and significant PV generation sold at a low export tariff during the summer due to the absence of battery storage. Case study 2 shows that the battery will charge during low-cost economy (7:00-10:30) from PV and discharge during expensive grid hours (19:00-22:00). However, in the winter, the system is dependent of the grid during the day for not charging the battery from the grid during low peak periods. For summer time there is still a huge PV generation exported at low tariff. Finally in case study 3 the battery charges with maximum power during periods of negative wholesale electricity tariff, minimizing grid electricity purchase.

2.4.1 Types of Tariffs

Energy companies have devised solutions to mitigate this consumption imbalance, offering various tariff options for customers to choose from. These tariff options aim to provide flexibility and cater to diverse consumer needs, contributing to a more balanced energy consumption pattern.

There are two regimes in Portugal:

1. **Free market supply to eligible consumers** - the supply is made by free market companies using freely negotiated conditions (except some Regulation terms defined by Regulatory Entity of Energy Services (ERSE));

2. **Supplier of Last Resort (SLR)** - This supplier must ensure specific consumers with regulated tariffs (yearly defined by ERSE). Additionally, the supplier is required to purchase all the electricity generated under special regime generation at fixed and regulated prices, varying according to the generation technology and operating under a feed-in tariffs scheme. Foles et al., 2020 indicates that SLR generators are not restrict from selling their energy to other suppliers.

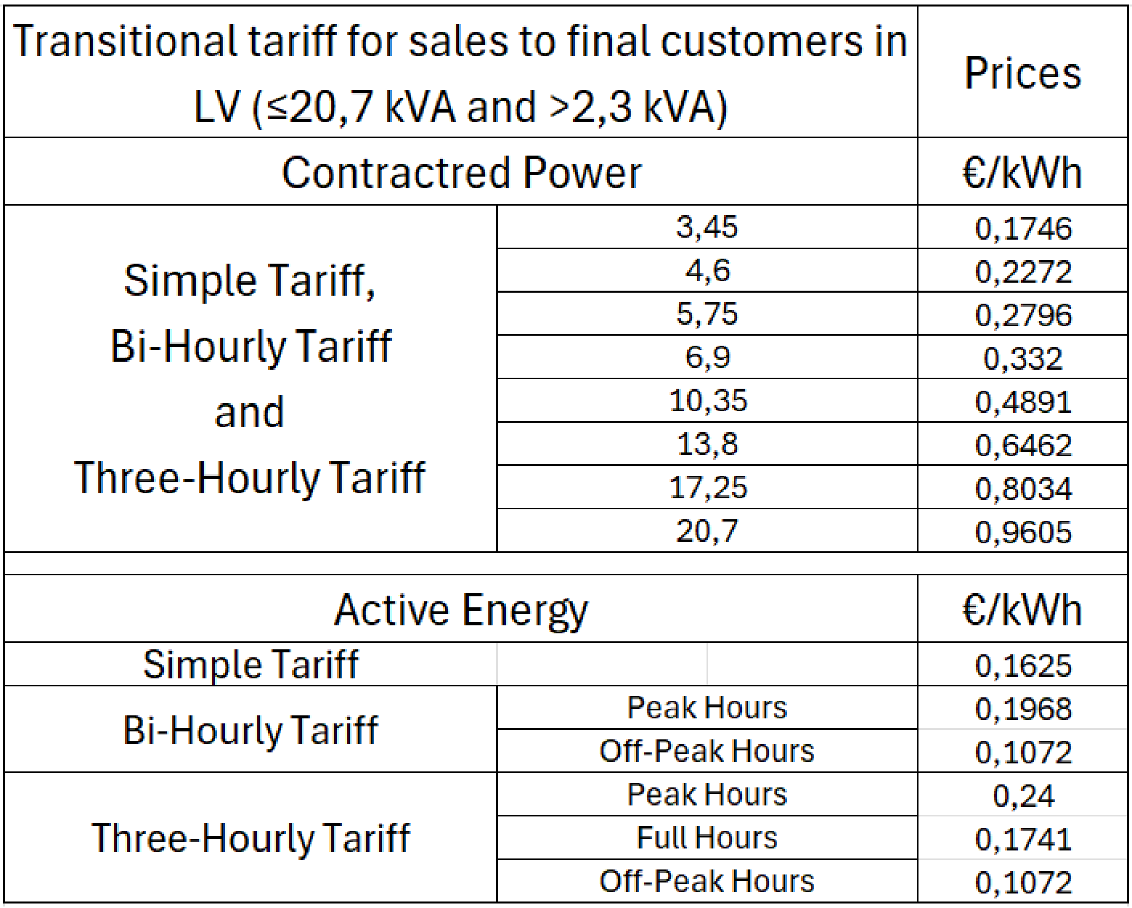
Notably, there are tariff structures where prices fluctuate daily, and for the purposes of this work, fixed, bi-hourly, and tri-hourly tariffs are particularly relevant. The overview provided in table 2.3 , sourced from ERSE, delineates the distinct tariffs applicable in 2024 for final customers in low voltage grid in Portugal.

As shown, in a fixed plan the cost stands at 0.1625€/Kilo Watt hour (KWh), presenting a potentially favorable choice when consumption needs aligns with high peak intervals.

In bi-hourly plan, customers can save some money when consuming in low peak intervals but it entails the risk of higher costs during high peak intervals, with rates of 0,1072€/KWh and 0,1968€/KWh for "Off-Peak" and "Peak" hours, respectively.

The tri-hourly plan closely resembles the bi-hourly variant but introduces an additional interval, offering three distinct prices based on consumption time, 0.1072€/KWh, 0.1741€/KWh and 0.24€/KWh for "Off-Peak", "Full" and "Peak" hours, respectively.

Table 2.3: Tariffs costs in BTN from ERSE (2025)



Transitional tariff for sales to final customers in LV (≤20,7 kVA and >2,3 kVA)		Prices
Contractred Power		€/kWh
Simple Tariff, Bi-Hourly Tariff and Three-Hourly Tariff	3,45	0,1746
	4,6	0,2272
	5,75	0,2796
	6,9	0,332
	10,35	0,4891
	13,8	0,6462
	17,25	0,8034
	20,7	0,9605
Active Energy		€/kWh
Simple Tariff		0,1625
Bi-Hourly Tariff	Peak Hours	0,1968
	Off-Peak Hours	0,1072
Three-Hourly Tariff	Peak Hours	0,24
	Full Hours	0,1741
	Off-Peak Hours	0,1072

This work aims to strategically leverage these tariff plans, with a preference for the tri-hourly structure, to optimize cost savings by charging the battery during low-cost empty hours and discharging it during high-cost peak hours if required.

2.4.2 Consumption Intervals

Electricity tariffs may differ when considering distinct time intervals as prescribed by ERSE, in Portugal. While these intervals, shown in Figure 2.6 and Figure 2.7, represent just one of many scenarios, they encompass weekdays, Saturdays and Sundays, accounting for both winter and summer seasons. "Super Empty" and "Normal Empty" will be considered as "Off-Peak" hours for calculations proposes as they do not impact the tariff types under examination.

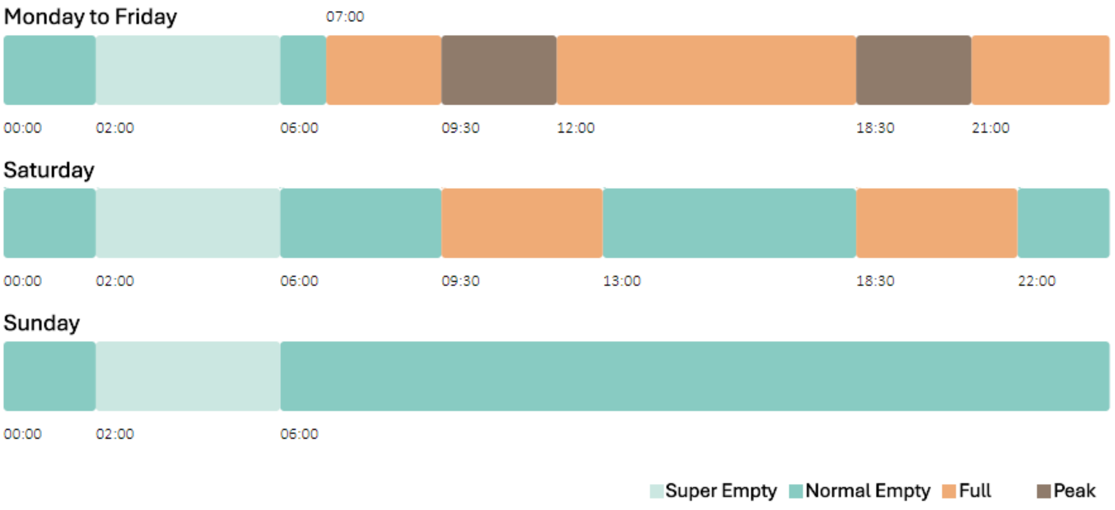


Figure 2.6: Winter schedule for weekdays, saturdays and sundays from ERSE (2025)

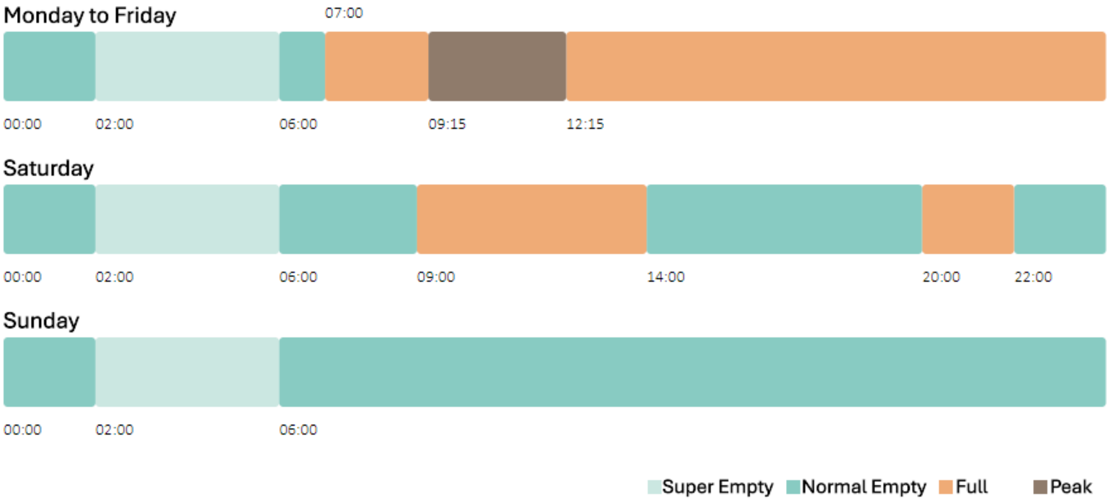


Figure 2.7: Summer schedule for weekdays, saturdays and sundays from ERSE (2025)

Combining this information with the earlier insights provided in Figure 2.5 and table 2.3 we can envisage potential cost savings associated with exclusive consumption during low peak intervals.

Let's assume a hypothetical household with an average consumption of 0.3KWh during low peak hours over 8 hours, 0.6KWh during full hours across 12 hours, and 0.75KWh during peak hours for the remaining 4 hours. Applying this consumption profile to a tri-hourly tariff, we project a monthly bill of nearly 70€ and more than 61€ when opting for fixed price profile. However, if we could charge a battery during low peak intervals, maintaining the same consumption average we can reduce that bill to 40€, realizing a possible cost reduction of 40%. It is essential to note that this serves as an illustrative example, and the values presented are not reflective of real-world data.

2.5 Energy Communities

An Energy Community is a group of individuals, families, or local institutions that work together to produce, consume, store and manage energy, typically from renewable sources at a local level and some of its benefits can be seen in table 2.4.

Table 2.4: Key benefits of energy communities

Benefit	**Description**
Local Empowerment	Engaging citizens in community energy schemes has the power to support constructive social norms and drive the transition towards sustainable energy behavior. Community energy has the power to empower citizens through enabling them to take part and decide in renewable energy, as highlighted in Commission et al. (2020).
Renewable Energy Generation	Energy communities often focus on the development of renewable energy projects such as solar, wind, or hydroelectric power. This contributes to a more ecologically, sustainable and environmentally friendly energy composition.
Cost Savings	Involvement in community-based energy projects can lead to cost savings. Collective investment and joint bargaining power can secure good deals on energy equipment and services, saving money. Additionally, sharing costs and risks eliminates the substantial upfront financial barrier for individuals, as discussed by Koirala et al. (2018).
Energy Independence	Energy communities promote a degree of energy independence by generating power locally. This reduces reliance on centralized energy sources and contributes to more resilient energy systems.
Economic Development	Energy communities can also play a relevant role in local economic growth and job creation. By boosting smart grid infrastructures, these communities provide valuable flexibility services that can be traded in emerging markets. This accelerates the transition towards a low-carbon economy, as highlighted by Koirala et al. (2016).
Community Cohesion	Energy communities foster a sense of community by bringing people together around a shared goal. Collaborative decision-making and shared benefits can strengthen social bonds.
Environmental Benefits	By focusing on renewable energy sources, energy communities contribute to the reduction of greenhouse gas emissions and help combat climate change.
Grid Support and Flexibility	Energy communities can enhance grid stability and flexibility. Decentralized energy generation and storage systems can provide support during peak demand periods and reduce stress on the grid.
Education and Awareness	Community energy projects raise awareness about sustainable energy practices and educate participants about the environmental and economic benefits of renewable energy.
Resilience	By diversifying energy sources and incorporating distributed energy resources, energy communities increase resilience against power outages and disruptions.

The aim of Energy Communities is to increase energy autonomy, reduce expenses, and enable environmental sustainability by involving citizens in the energy transition. Citizens and communities actively engaging as partners in energy projects are reshaping the energy system. This concept has gained significant attention in recent years, leading to the development of diverse practices for the management of community energy projects, as discussed in Commission et al. (2020).

As said before, it is expected to have around 80% of energy from renewable sources by 2050 and it is also expected that half of all European households would be involved in renewable energy generation, 37% of which should be engaged in collective projects.

2.5.1 Second-Life Batteries in Communities

Returning to the discussion on tariffs, energy consumption was noted as exhibiting semi-predictable behavior, given that not everyone utilizes electricity simultaneously. However, in community settings, we often observe a more predictable and linear energy consumption pattern, offering a more straightforward model and control framework, as mentioned by Reis et al. (2021).

Additionally, as discussed previously, the concept of second-life batteries, used EV batteries that have reached the end of their automotive lifecycle but can still find purpose in other applications, such as photovoltaic systems. Nevertheless, a challenge arises in certain locations where the average household consumption is not sufficiently high when compared to the capacity of an EV battery, as highlighted by Colarullo and Thakur (2022). This mismatch results in suboptimal utilization and an extended period for the return on investment.

Synthesizing these aspects, communities should be considered in this work, aiming to address these challenges and enhance the efficiency and viability of the proposed system. The integration of community-based energy consumption patterns and second-life batteries could lead to more effective energy utilization and a faster return on investment.

In energy communities, batteries serve as centralized storage systems that manage energy flows between consumers and the electrical grid, as mentioned by Colarullo and Thakur (2022). Typically, all electrical interactions, including those involving the community battery, are mediated through the grid, with individual users lacking direct access to the battery, since every energy interactrion is made through the electrical grid. Integrating second-life EV batteries into energy communities, with all interactions managed through the electrical grid, offers a promising pathway to enhance energy efficiency and sustainability. This strategy not only optimizes the use of existing resources, but also promotes environmentally friendly energy infrastructure.

2.6 Technologies and Models

2.6.1 Rule-Based Systems and Case-Based Reasoning

A Rule-Based System (RBS) operates by employing rules created by individuals to store, sort, and manipulate data, essentially simulating human intelligence. These systems rely on a collection of facts, data, and rules to perform data manipulation. The rules within these systems can be called "If Then Statements", as they adhere to the logic of "If X occurs, then execute Y", as described by Santos (2023). An article from Camblong et al. (2024) details how a rule-based energy managment system can maximize PV self-consumption to an 89% rate by controlling HVAC loads based on rules established for solar generation and comfort needs.

In the context of energy management, a rule might dictate that during off-peak hours, the system should prioritize charging the battery using electricity from the grid at lower costs. While RBS provides a structured, easy and deterministic approach, it has limitations such as rigidity and limited learning. RBS can be rigid and struggle to adapt to dynamic or unforeseen situations not covered by predefined rules and they lack the ability to learn and evolve from experience, making them less effective in scenarios envolving user behaviors or changing environmental conditions.

Since this thesis will have to cover different consumption profiles, a rule-based system would not be effective and for that there is a need to envolve another system, case-based reasoning.

Case-Based Reasoning (CBR) allows a system to learn from experience. In the context of energy management, CBR involves the system analyzing historical cases, such as past energy consumption patterns and corresponding decisions. For instance, it might learn that certain users tend to consume more energy during weekends. This learning process helps the system make more informed and context-specific decisions over time. Faia et al. (2017) implemented a CBR methodology with swarm optimization and expert systems that retrieves and adapts case histories such as past energy saving profiles to tailor load reduction strategies that keep occupants comfortable while enhancing efficiency.

As RBS alone lacks adaptability and CBR alone may lack foundational safety rules and potentially risking rule violations, combaning the two ensures the system to stay within safe and efficient boundaries, learns and personalizes over time and remains robust across a variety of consumption profiles. This hybrid approach will bring several advantages:

- **Flexibility** - The combination will allow the system to have default rules to start with, providing a stable structure, while learning from cases over time to adapt to unique situations.

- **Adaptation to User Behavior** - CBR enables the system to adapt to individual user's behaviors and preferences, providing a personalized and user-centric approach to decision-making.

- **Efficiency** - RBS deals with routine and well-defined scenarios, while CBR deals with specific new behaviors, resulting in greater effectiveness in solving problems
- **Continuous** Learning - The system can continuously learn and update its knowledge base, ensuring that it remains relevant and effective in dynamic environments.

By integrating rule-based systems and case-based reasoning, an energy management system can benefit from the strengths of both approaches, providing a more versatile, adaptive, and efficient solution for predicting energy consumption and making informed decisions about energy provision.

2.6.2 Batteries Degradation Methods

As mentioned in subsection 2.3.1, battery SoH is a huge factor in this thesis since it's mandatory to have a precise information on that in order to estimate battery percentage state. This information is required to use in the monitoring system so it can evaluate needs and optimal energy approaches.

To demonstrate the feasibility of SoH estimation, Figure 2.8 illustrates the division of current SoH estimation methods based on the taxonomy developed by Tian et al. (2019). These have classically been divided into two broad groups: Voltage-based methods and Other signal-based methods. The last includes OCV, impedance, and electrochemical methods, while the former employs signals such as temperature, ultrasound, or force.

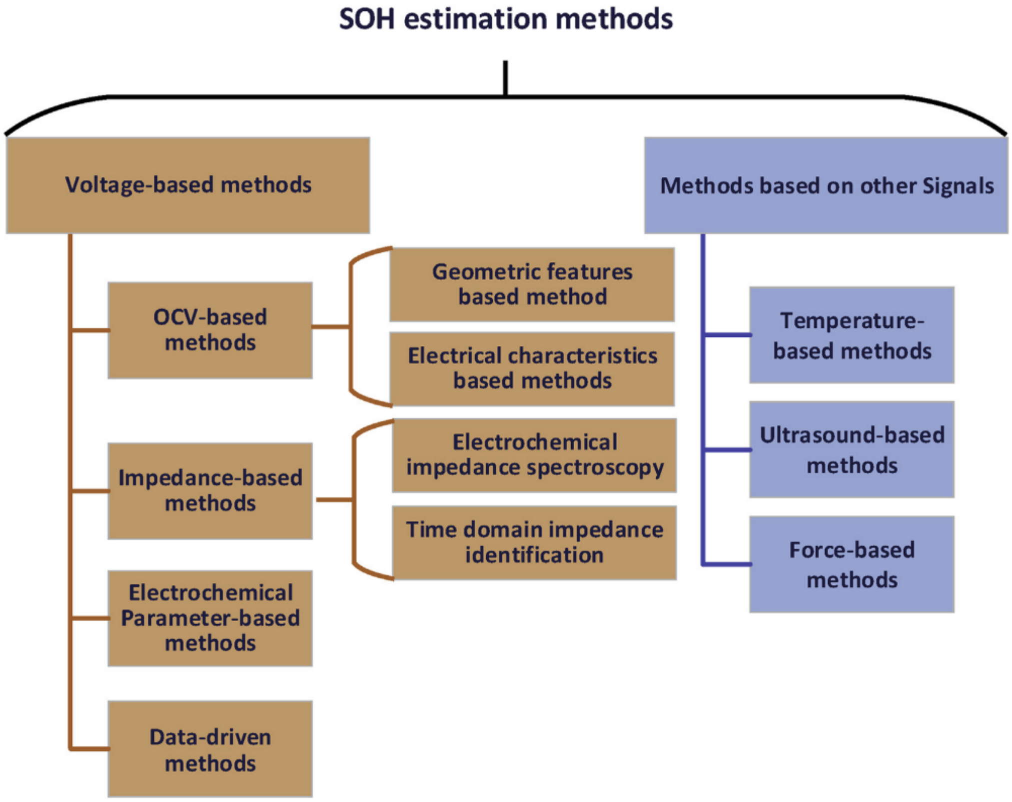


Figure 2.8: Classification of SoH estimation methods from Tian et al. (2019)

With the addition of this overview, the intention is to advance the point that various well-known methods are actually available to estimate battery SoH, and that these can be implemented in energy management systems. This serves to validate the assumption made in this dissertation that SoH data can be easily acquired and used in practice, either directly from battery management systems or as embedded sensing mechanisms.

2.6.3 Fuzzy-Based Charging-Discharging

Lithium-Ion batteries can have different rates of charge and discharge depending on their cells, however the typical maximum charge rate is 1C and 2C for discharge rate. Charge and discharge rates of a battery are governed by C-rates. The capacity of a battery is commonly rated at 1C, meaning that a fully charged battery rated at 1Ah should provide 1A for one hour. This is important to consider since certain batteries may not be able to provide huge amounts of energy and that's something to keep in mind when simulating and modeling the system.

There are various models to control a lithium-ion battery, for example a fuzzy-based method used by Faisal et al. (2021), where it presents a fuzzy-based charging-discharging controller for lithium-ion batteries in microgrid applications.

The proposed fuzzy-based scheme considers factors such as available power, load demand, and battery State-of-Charge (SoC) to enable the storage system to charge or discharge within a safe operating region, preventing over-charging or over-discharging and providing a simpler and faster alternative to traditional control techniques.

Various controlling techniques for battery performance have been explored in the literature, each with its limitations. For instance, droop control and Model Predictive Control (MPC) are widely used in battery management, but these types of strategies typically involve advanced mathematical models, could be computationally costly, or lead to slow dynamics in real applications. The article introduces a Fuzzy Logic Controller (FLC) for charging-discharging operations, emphasizing its ease of implementation, lack of complex mathematical calculations, and quick response. The proposed FLC is compared with other controlling techniques, demonstrating its superiority in controlling battery SoC within the safe operating region.

The proposed fuzzy controller is tested through numerical simulations, demonstrating its effectiveness in controlling battery charging and discharging in response to load variations. The article also describes an experimental setup using an Arduino platform and lithium-ion battery storage to validate the fuzzy controller's real-time performance. The experimental results confirm the controller's ability to maintain SoC within the safe operating region.

As so, fuzzy-based technique will be adequate for this work with a few adjustments to be made.

2.6.4 Energy Communities Methodologies

According to Reis et al. (2021) there are three energy business models. Let's analyze each model and highlight some topics to compare them:

1. **Customer-side business model** - Involves end-users directly purchasing energy technologies to become prosumers or take advantage of Demand-Side Management programs, also mentioned by Bakare et al. (2023).
    - Power purchase agreements or feed-in-tariffs for surplus generation.
    - Technologies like solar PV and micro wind turbines.
    - High upfront costs and long payback periods.
2. **Third-party-side business model** - Fully financed by third-party companies utilities, which own and control assets to provide valuable energy services.
    - Renewable energy supply and DSM-based services.
    - Aggregating customer's demand flexibility.
    - Long-term contracts between customers and investing companies.
3. **Energy community business model** - Created by citizen groups aiming for collective energy projects with a focus on local generation, supply, storage, consumption, and more.
    - Financial involvement from community members.
    - Return on investment through cheaper energy supply, surplus generation, or participation shares.
    - Social and environmental contributions.
    - Another article, from Mohammadi (2023), explores energy community models, emphasizing the importance of supportive policy instruments, institutional frameworks, and citizen governance

These business models offer diverse approaches to energy management, ranging from individual prosumer initiatives to utility-driven services and community-driven energy projects. While each model has its own set of advantages and challenges, exploring a hybrid approach that combines elements of Customer-Side and Energy Community models could provide a synergistic solution. This hybrid model aims to empower citizens with affordability, independence, and flexibility, fostering a more resilient and sustainable energy ecosystem.

2.6.5 Research Summary

This work focuses on optimizing SHEMS by integrating various techniques and methodologies previously studied, with additional enhancements.

Primarily, Inês Santos (2023) has developed a real-time monitoring system for home appliances, incorporating predictive models to facilitate decision-making. In this work, the system will be adapted to include batteries and energy tariffs as additional decision-making parameters.

Accurate monitoring requires consideration of physical system degradation and losses. There is also various studies that has shown some methods to estimate SoH of a battery and studies about PV efficiency. Precise knowledge of available energy and battery health is crucial for seamless system operation.

For simulation purposes, a study about LIB charge and discharge controller was found, where the author tests a fuzzy-based system to control a battery. This approach has shown to be very effective and accurate and will be adapted to be used in this work since its imperative to know the battery charge and discharge rate capacity as it should be enough to cover user's necessities.

For the battery, studies have shown that SLB emerge as cost-effective options for this type of application. Some studies also tested and confirm that a healthful SoC must be maintained to optimize battery lifespan. This dissertation will adapt, through simulations, second-life batteries from EV, controlling them to maintain a 15%-65%SoC range to achieve longer lifetime.

Various studies about energy tariffs were made to find the best methods for every specific scenario. This dissertation will consider a scenario involving battery storage, exploring grid interactions for charging purposes if deemed economically viable.

Lastly, insights from studies on energy communities reveal both benefits and challenges. Energy communities will play a significant role in this dissertation, offering more predictable consumption patterns, affordable installations and increased flexibility.

3

CONCEPTUAL APPROACH

This chapter is dedicated to the foundational concepts that have shaped the development of this dissertation proposal - the WattFuture[1] System, outlining the key methodologies, frameworks, and approaches adopted to address energy management challenges in community-based photovoltaic systems.

3.1 Overview

Prior to exploring the technical specifics of the suggested system, it is important to give a short summary. The central concept involves gathering and leveraging comprehensive data from every household to create a precise predictive model that can project future energy consumption and generation. This predictive capability allows for optimized energy management, improving efficiency and reducing costs.

The collected data is stored in a local database to ensure privacy and capture the unique energy behaviors of each household. Using this data, the system generates a structured table, referred to as a dataframe, that includes essential information such as forecasted consumption, energy production, and, with the help of an Application Programming Interface (API), Open-Meteo (2025), future weather conditions. This structured data is then fed into the WattFuture Model, which evaluates the optimal energy source for each time interval, considering electricity prices and anticipated energy demand.

To enhance energy management efficiency, the system incorporates a battery storage package, which provides flexibility and minimizes overproduction from photovoltaic PV installations. The battery system should be implemented in order to reduce installation complexity, minimize infrastructure costs and allow centralized control. Therefore, rather than being directly connected to individual households, the battery is linked to the electricity grid, as illustrated in Figure 3.1.

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[1] The name WattFuture embodies the vision of anticipating future energy needs to proactively address them-"Powering Tomorrow, Today."

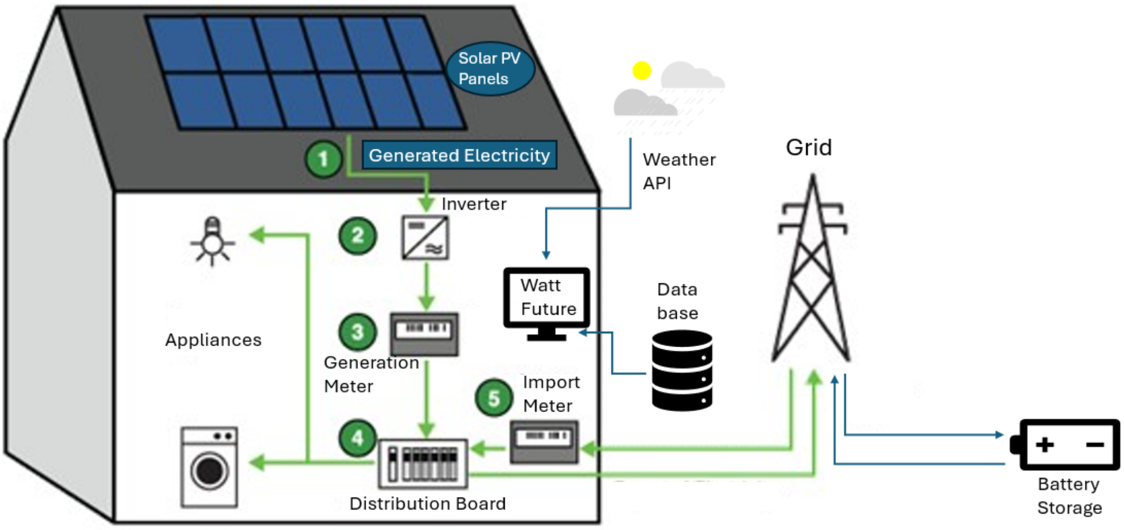


Figure 3.1: WattFuture Illustration

Figure 3.1 provides a simplified representation of the proposed system. The design allows users to manage their energy consumption efficiently, with minimal intervention, while also offering tools for manual management, enabling greater control over household energy usage.

To clarify the system's operation, consider two scenarios:

1. **Automatic Energy Management** - If a user prefers not to be actively involved in energy management, the system autonomously calculates energy consumption and production to achieve the most efficient energy distribution within its constraints. For instance, if a user consistently does laundry during high-peak hours without concern for energy costs, the WattFuture Model will detect this behavior over time. The model will then preemptively save energy in the battery for use during those high-cost hours, optimizing energy expenses.

2. **Manual Energy Management** - If the user chooses to play an active role in energy management, the system allows for manual input of known energy consumptions. For example, if the user knows they need to do laundry and charge their electric vehicle the following morning, they can input this information into the system. The WattFuture Model will incorporate these consumptions into its predictions and assess whether it is more cost-effective to charge the battery beforehand, ensuring energy availability at the required time.

This dual approach automatic management and user driven adjustments, ensures that the system is both user friendly and adaptable to individual preferences. The integration of predictive models, battery storage, and grid connectivity makes the WattFuture system an efficient and innovative solution for energy communities.

The following subsections will take a closer look at figure 3.1.

3.1.1 Monitoring System

Firstly, the monitoring system, represented as WattFuture for this thesis, is based on the system developed by Inês Santos (2023). Her work uses a knowledge-based system to analyze data and take decisions as it is considered a form of artificial intelligence that focuses on capturing the knowledge of human experts to support decision making. This system requires knowledge base containing domain specific information such as facts, rules and heuristics, an inference engine to process the information in the knowledge base to draw conclusions and take decisions and a user interface to allow interaction between the user and the system.

This dissertation will also be using some tools like Rule-Based Systems and Case-Based Reasoning, details in Subsection 2.6.1, to allow the monitoring system to make decisions.

3.1.2 Grid and Community System

In this thesis, the grid facilitates the connection between households, photovoltaic PV systems, and the shared battery storage, ensuring that all energy interactions occur seamlessly and efficiently.

The grid's role includes:

- **Energy Exchange** - Acting as the medium through which excess PV energy is exported and redistributed to meet demand across the community.
- **Battery Integration** - The shared battery storage is connected to the grid, allowing for flexible energy storage and discharging, accessible to all community members.
- **Stability and Backup** - By connecting the system to the grid, households benefit from a reliable energy supply during periods of low solar production or unexpected demand spikes.

The grid also ensures that no single household has direct control over the shared battery storage, enabling fair and balanced energy utilization within the community. This centralized approach not only improves energy efficiency but also enhances the economic viability of the system by leveraging grid-based energy prices and demand balancing.

3.1.3 Data Acquisition

When the main goal is to work on predicted values, historical data is fundamental and the more the better. For this thesis there is a need to have a base database to get a default predictive model that will be adapted to each user after some time. E-REDES, Portuguese electricity distribution system operator, gives access for users that have an intelligent meter to a website that contains historical consumption data.

WattFuture's success relies on consumption data so it is crucial to have a considerable amount of information. One of WattFuture features is to let users add their historical consumption data to improve their predictive model. This data from E-REDES comes in an Excel format with four relevant columns, being them:

- **Date** - Providing the year, month and day in 'YYYY/MM/DD' format.
- **Time** - Providing the hour and minute in 'HH:MM' format, every 15 minutes.
- **Consumption** - Providing the consumption in kW.
- **State** - Providing the information on whether that consumption was real or calculated.

Regarding the weather data acquisition, WattFuture will use an API to retrieve accurate information based on the personal information about the user such as location. This API will return helpful information, i.e. irradiance and temperature, to calculate power production from the PV panels.

After installing WattFuture and feeding in historical data, if available, the idea is to continuously collect consumption values directly from the smart meter, avoiding dependence on external sources and manual labour.

3.2 Requirements

A website must be developed to enhance user interaction with the system, making it easier to modify settings, update models and view results. This website is used by users with different statuses to improve security.

- User - Regular user who owns one or more households with the ability to get an overview of its installations but has not permissions to change their settings. This agent can only change personal settings such as number of habitants.
- Admin - A qualified user who can manage global settings, from updating battery/PV specifications to manage communities.
- System Timer - Responsible for automation and internal updates.

Table 3.1 outlines all the functionalities provided by the website.

Table 3.1: WattFuture's System Requirements

Req. ID	**Function Description**	**Actors**
R1	The system must allow account creation and log in.	User, Admin
R2	The system must allow admin users to edit PV and battery specifications.	Admin
R3	The system must allow all users to update the predictive model.	User, Admin
R4	The system must allow all users to refresh their energy predictions.	User, Admin
R5	The system must allow all users to refresh their energy sources.	User, Admin
R6	The system must automatically update the predictive model.	System Timer
R7	The system must automatically update predictions.	System Timer
R8	The system must automatically update energy sources when predictions are created or updated.	System Timer
R9	The system must allow users to view the predictions created.	User, Admin
R10	The system must allow users to view the predicted model metrics.	User, Admin
R11	The system must allow users to view the energy sources.	User, Admin
R12	The system must allow users to add their households.	User, Admin
R13	The system must allow all users to edit their households.	User, Admin
R14	The system must allow the creation of energy communities between households that shared the same battery.	Admin
R15	The system must allow admin users to edit/delete communities.	Admin
R16	The system must allow all users to add future known consumptions.	User, Admin
R17	The system must allow all users to add historical consumption data.	User, Admin

Figure 3.2 represents the interactions between agents for each requirements.

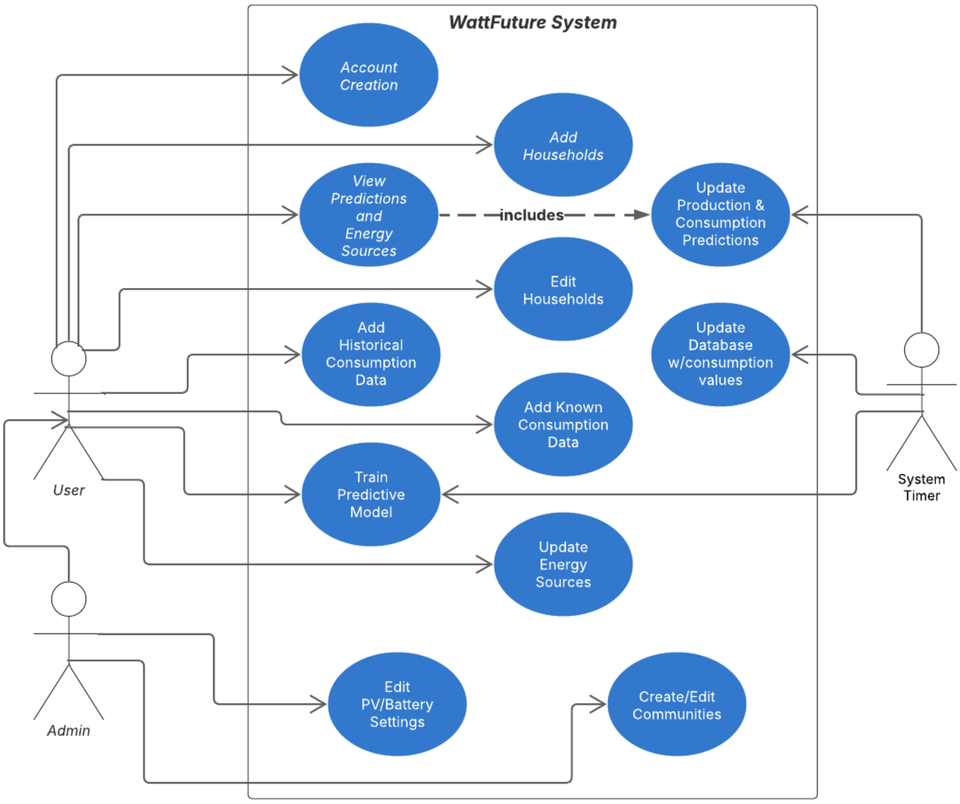


Figure 3.2: UML Use Case Diagram

Given that this thesis is designed to serve both independent households and energy communities, it is necessary to impose certain limitations on website capabilities. These limitations are essential to prevent users from altering the specifications of installations that are being utilized by other households. To address this, an admin role was implemented, granting only admins the authority to modify installation specifications.

Apart from that, the system must allow only admins to create valid communities, meaning that it is only acceptable households with the same battery ID, otherwise it would not make sense to share electricity among them. Regarding PV panels, there is no limitation for the community, each household can have their own installation and it may vary from others.

The system should be able to accept energy consumption data from the users, whether from historical files or from known consumptions like charging a car every day at a specific hour. This functionality will help the system to quickly adapt to the user's behaviors.

3.3 WattFuture Conceptual Architecture

A well-structured architecture is crucial for the success and seamless implementation of WattFuture. The system is composed of four primary layers, each serving a distinct function within the overall framework.

The following figure 3.3 represents the system's architecture.

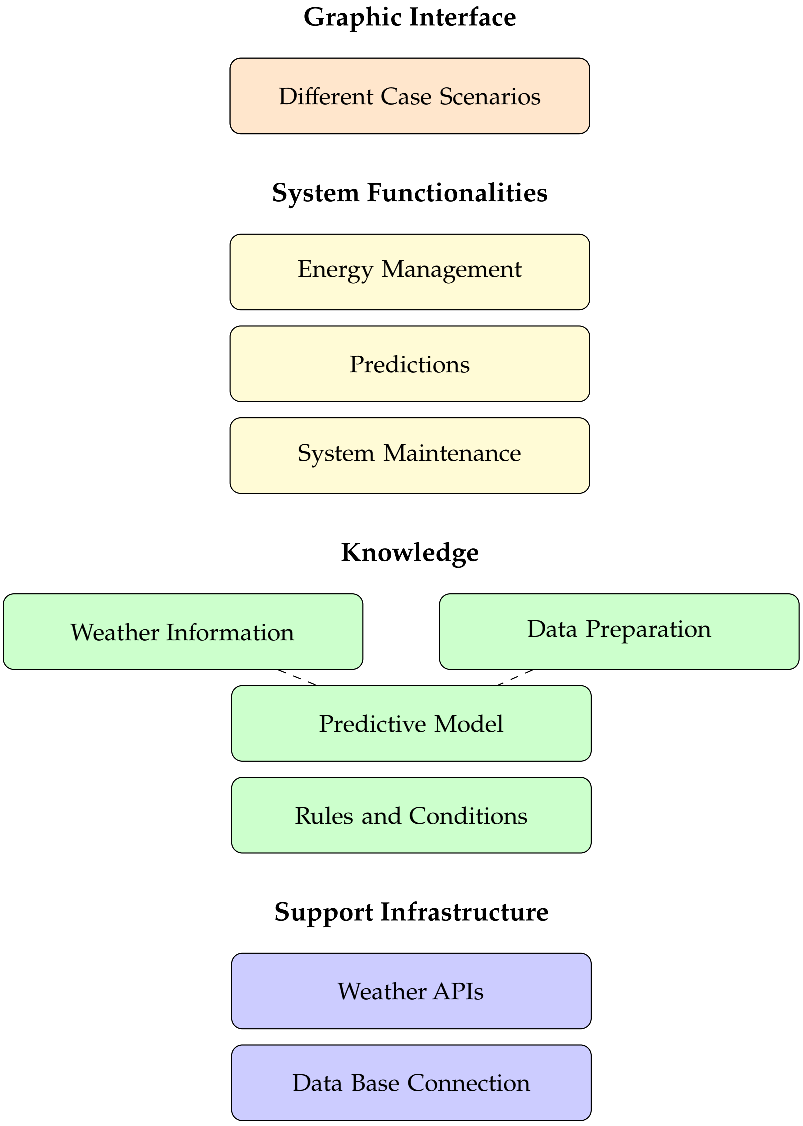


Figure 3.3: WattFuture Conceptual Architecture

The support structure layer is responsuble for establishing the relationships between models and managing the connection to external APIs. The API plays a vital role in this architecture by enabling communication and data exchange. Specifically, it retrieves real-time weather data for each household, providing a critical input for the predictive model. This weather data serves as a foundational element, offering necessary context for accurate energy consumption forecasts.

The knowledge layer is dedicated to the creation and refinement of the predictive model. This model, built on the historical data stored within the database, is used to predict future energy consumption values. Additionally, this layer should incorporate an intelligent model, able to optimize energy management and able to identifying the best energy sources based on the predicted consumption. Unlike rule-based systems, the model implemented leverages constraints to provide greater flexibility, allowing it to analyze multiple scenarios and identify the most effective energy strategy.

The system functionalities layer encompasses all system functionalities, orchestrating the interactions between various components to achieve the system's objectives. This layer acts as the backbone of the system, ensuring that the different modules and services work in harmony to deliver the expected outcomes, such as updating predictions, managing energy sources, and executing optimization algorithms.

The graphic interface layer is the user interface, which provides a graphical environment for users to interact with the system. Through this interface, users can manage households, modify PV and battery specifications, and visualize the results of various energy scenarios. The interface presents the outcomes of four key scenarios:

1. **Only Grid** - A baseline scenario to compare the cost of using only the grid for energy supply.

2. **Grid and PV Installation** - A scenario that incorporates a PV installation, with provisions for selling excess production back to the grid.

3. **Grid, PV Installation and Battery with no control** - A scenario that includes both a PV installation and a battery, where excess production is stored in the battery for later use when production does not meet consumption.

4. **Grid, PV Installation and Battery with Control** - A scenario where WattFuture optimizes the system by actively managing energy sources and storage to maximize efficiency and minimize costs.

These layers work together to provide a robust and stable architecture that effectively predicts energy consumption and optimizes the use of energy sources. The integration of these components ensures that the system is able to forecast future energy needs and to implement the best strategies to meet those needs efficiently.

3.4 Challenges and Considerations

While the proposed energy management system offers innovative solutions to improve energy efficiency in community settings, several challenges and limitations must be addressed to ensure its effective implementation.

The system relies heavily on household consumption data, weather forecasts, and user inputs to build predictive models. Nonetheless, this brings up a few issues:

- **Data Accuracy** - Partial or incorrect user information can diminish the performance of the predictive model Lee et al. (2024).
- **Privacy** - Managing and examining household energy information demands meticulous attention to guarantee user confidentiality and adherence to data protection laws.

Second-life batteries, although economical and environmentally friendly, have certain constraints that require more attention than a new battery:

- **Capacity Reduction** - Over time, battery capacity diminishes, limiting its capacity to store and discharge energy effectively. Li et al. (2021)
- **Maintenance Costs** - Regular monitoring and maintenance are required to prolong battery life, adding operational costs.

WattFuture relies on the electricity grid for battery connectivity and energy exchange. This introduces certain challenges:

- **Grid Outages** - In the event of a power outage, the shared battery system might fail to deliver energy to the community since it is connected to the grid and not directly to all households.
- **Tariff Variability** - Fluctuations in grid electricity prices could impact the system's economic efficiency.

As the number of households in the community increases, the system may face challenges in scaling up, as mentioned by Lee et al. (2024):

- **Computational Complexity** - Managing large amounts of data and optimizing energy distribution for numerous households can increase computational demands.
- **Interoperability** - Ensuring compatibility with different PV systems, inverters, and battery technologies adds complexity.

Managing fair access to the shared battery storage presents a significant challenge. Since, in an energy community, the battery is connected to the grid and serves multiple households, determining who gets energy and when can be complex. Key challenges include:

- **Prioritization** - Deciding which household receives energy during peak demand or limited storage.
- **Conflict Management** - Balancing energy access in cases where multiple households require energy simultaneously.

Addressing these challenges through thoughtful design, advanced algorithms, and user-centric approaches will be critical to ensuring the success and scalability of the WattFuture energy management system.

4

System Implementation

This chapter shows the implementation details of WattFuture, presenting the frameworks, methodologies and tools employed to translate the conceptual ideas into a functional system. This chapter will cover every software and technologies that have been used and the reason behind these choices, from choosing the framework, database, programming language, and additional components.

The following figure 4.1 illustrates a graphical view of how WattFuture was implemented.

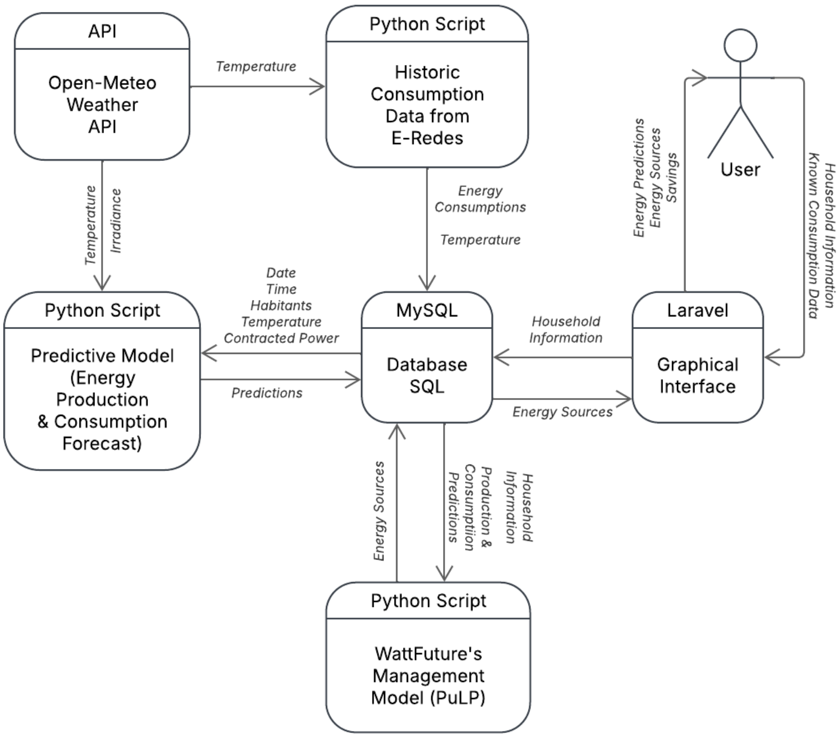


Figure 4.1: WattFuture's System Implementation

Each user will interact with Laravel (WattFuture's website) to provide crucial information about their households. Contracted power, number of habitants, PV and battery installation are a few examples of the information that is indirectly being inserted into the database by the user.

The weather API provides temperature and irradiance values for two different Python scripts. One script is responsible for reading excel files (provided by E-Redes), collecting temperature data from the API and generating the historical consumption data of the user. This data will be stored in a "consumptions" table in the database. The other script is responsible for providing energy predictions. For that, the script needs the temperature and irradiance information from the API and the household information stored in the database, previously provided by the user and the excel script. The script ends by storing the energy predictions in the database as "predictions" table.

After the database is fed with the energy predictions values, another Python script can then retrieve this information and the household information to feed into the Python Linear Programming (PuLP)'s model. This model is responsible for creating the energy sources table and store it in the database.

Finally, the Laravel interface enables users to view the predicted energy sources, savings, and other relevant metrics in an accessible format.

4.1 Database

In the initial stages of this project, MySQL was used as the primary database management system. MySQL's reliability and compatibility with Python, through Jupyter notebooks, facilitated the early development and testing of key features, such as energy consumption predictions and historical data analysis.

As the project advanced and the range grew, a switch to the Laravel framework was implemented. The reason for this change was the necessity for a development environment that could handle the increasing complexity of the system in a more integrated way. The Eloquent Object Relational Mapping (ORM) in Laravel offers a more user-friendly and effective method for handling database operations, including benefits like query creation, relationship handling, and smooth incorporation with the entire web application.

4.1.1 Database Overview

The database structure is designed to support the efficient management of energy systems by organizing data across multiple interconnected tables. This section outlines the purpose and relationships of key tables, emphasizing their role in the system's functionality.

The Seasons table, shown in the figure 4.2 plays a key role in managing temporal classifications of the year, which is crucial for energy tariff determination. Each entry in this table contains the start and end dates for a specific season, as well as its identifier and descriptive label. This data is foundational for retrieving the relevant tariffs from the Timezones and Electricity Prices tables as different seasons have different timezones and, consequentially, different electricity tariff prices.

Figure 4.2: Seasons Table

From the seasons table we retrieve the season in question and, since the current electricity tariffs only differentiate between summer and winter, there is a need to convert both spring and autumn seasons to summer and winter, respectively.

After this conversion, the timezones table establishes a direct relationship with Electricity Prices, represented in figure 4.3, mapping time-based attributes like the day of the week and hourly intervals to specific tariffs. By leveraging these connections, the system ensures accurate pricing for energy usage throughout different periods. This layered approach allows the energy system to dynamically adjust to seasonal and temporal fluctuations, optimizing its cost-effectiveness.

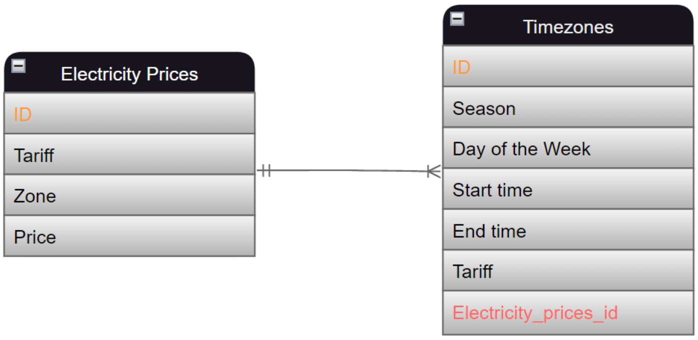


Figure 4.3: Timezones and Electricity Prices Tables

The Households table serves as a central entity representing each home from each user of the energy system. Figure 4.4 shows that each household record includes attributes like:

- **Habitants** - Number of people living in the household.
- **Location** - Latitude, longitude, and descriptive details.
- **Tariff Information** - The energy pricing plan assigned to the household.
- **Contracted Power** - Household's contracted power plan.
- **Energy Infrastructure** - Foreign key references to the Battery and PV Installation tables.

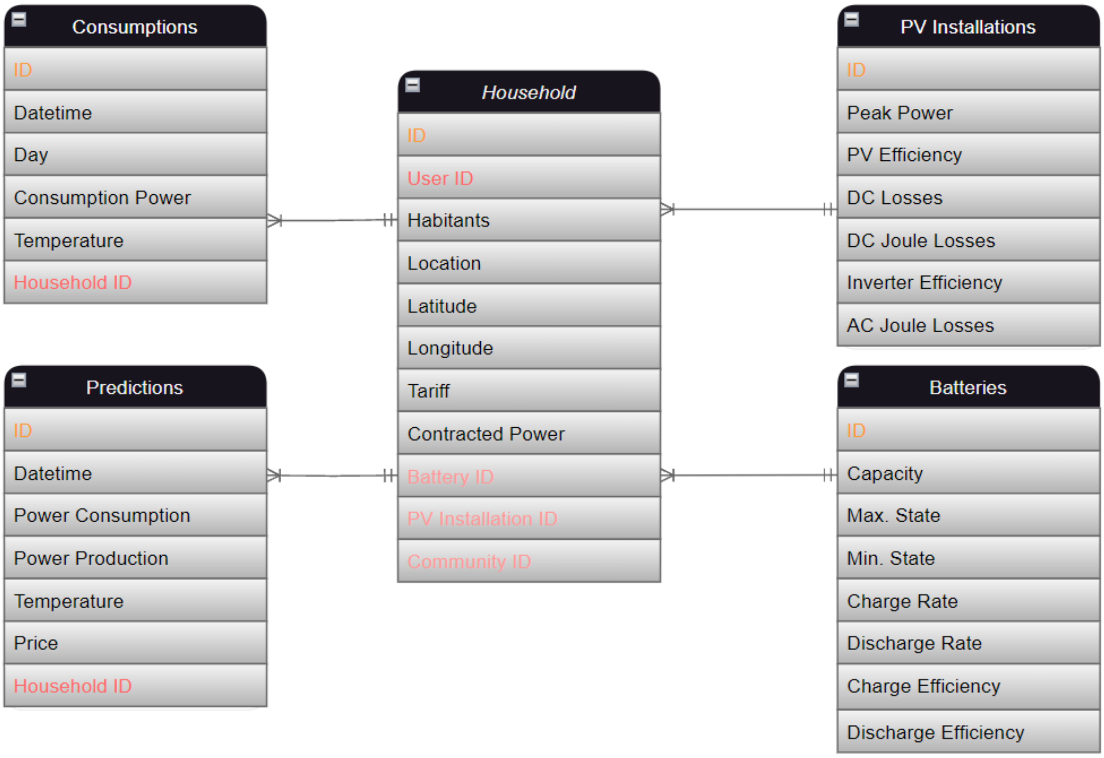


Figure 4.4: Household table and its relationships

Figure 4.4 reveals that each household may have several consumptions and predictions, and, at the same time, multiple households can share PV or batteries installations.

The relationship with the Communities, illustrated in the figure 4.5 table enables the grouping of multiple households under a single energy community. This is fundamental in managing shared resources, such as a community battery.

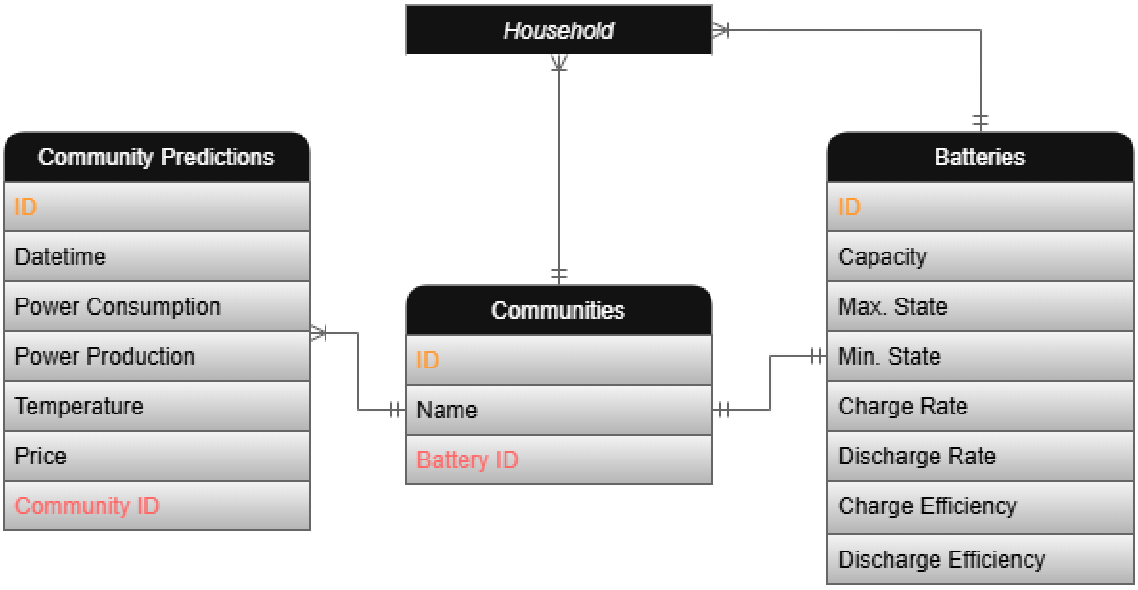


Figure 4.5: Communities table and its relationships

Additionally, the Energy Source and Community Energy Source tables records data on energy usage and production for each household or community. Key attributes include:

- **Energy Consumption and Production** - Tracking how much energy is used or generated by the household/community.
- **Energy Storage** - Fields for battery usage, grid usage, and charging rates reflect the energy flow between the grid, batteries, and PV installations.
- **Pricing** - Captures the cost associated with energy usage during specific intervals.

Figure 4.6 illustrate both Energy Source and Community Energy Source tables:

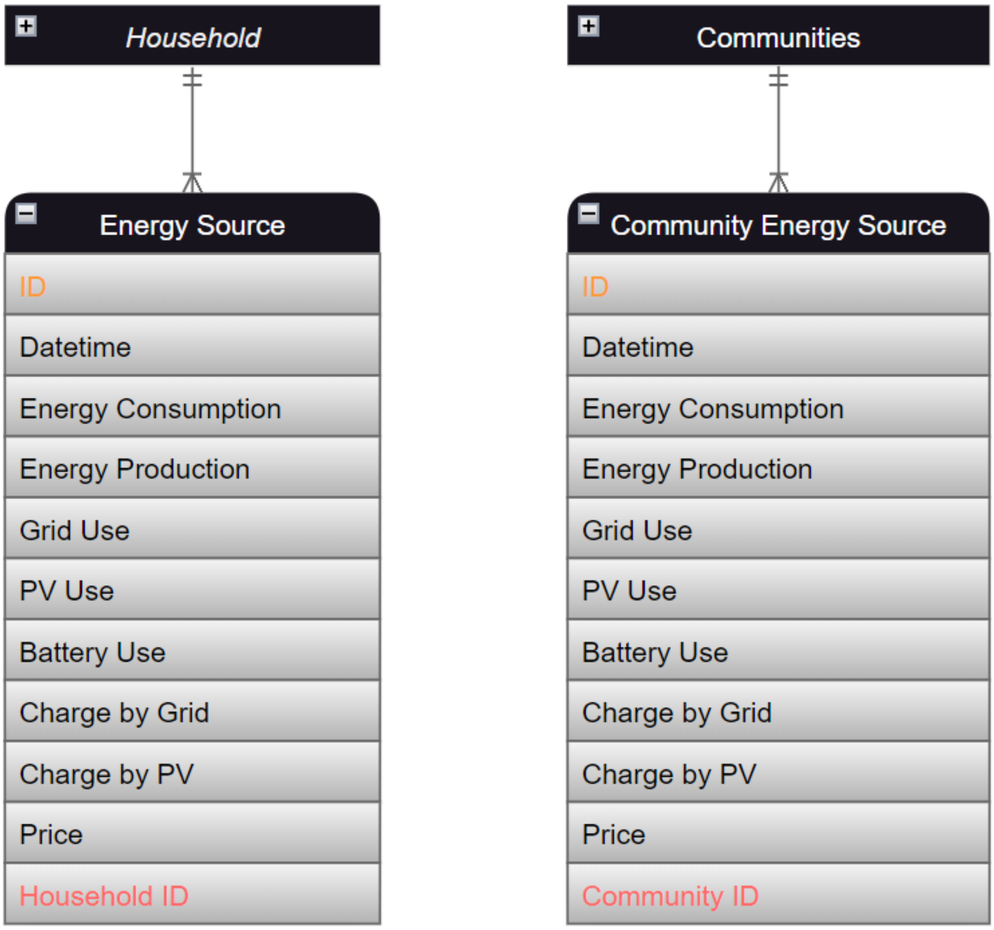


Figure 4.6: Energy Source Tables

4.1.2 Laravel's Migrations

The current database schema, implemented within Laravel, includes tables for users, households, predictions, and energy sources, among others. Laravel's migration and seeding tools were instrumental in maintaining version control and ensuring consistency across different environments. This transition has not only streamlined the development process but also improved the scalability and maintainability of the database.

Each migration file in the system corresponds to a specific change in the database, allowing for smooth transitions during development. The use of migrations offers the following advantages:

- **Version Control** - Ensures the database schema remains consistent across development environments.
- **Rollback Capability** - Provides the ability to reverse changes, reducing risks during updates.
- **Seamless Deployment** - Facilitates database updates in production with minimal downtime.

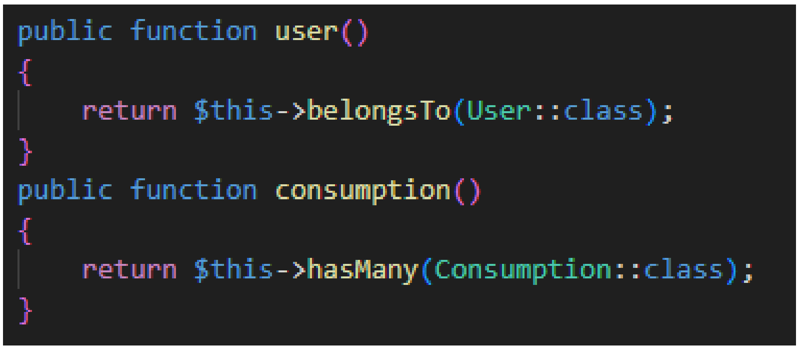
The following figure 4.7 provides an example of a migration, in this case, the households migration.

```php
class CreateHouseholdsTable extends Migration
{
    public function up()
    {
        Schema::create('households', function (Blueprint $table) {
            $table->id();
            $table->integer('habitants');
            $table->string('location', 45);
            $table->integer('location_id');
            $table->float('lat');
            $table->float('lon');
            $table->integer('tariff');
            $table->float('contr_power');
            $table->unsignedBigInteger('battery_id')->nullable();
            $table->unsignedBigInteger('pv_installation_id')->nullable();
            $table->timestamps();

            $table->foreignId('user_id')->constrained()->onDelete('cascade');
            $table->foreign('battery_id')->references('id')->on('batteries')->onDelete('set null');
            $table->foreign('pv_installation_id')->references('id')->on('pv_installations')->onDelete('set null');

        });
    }

    public function down()
    {
        Schema::dropIfExists('households');
    }
}
```

Figure 4.7: Households Migration Example

With the creation of migrations it is possible to create dynamic relationships between tables using Eloquent ORM. Laravel's Eloquent ORM simplifies the interaction with the database by abstracting complex SQL queries. Relationships such as one-to-many or many-to-many are defined as methods in the corresponding models.

For example, the relationship between households and users or households and consumptions is illustrated in the following figure 4.8.



```
public function user()
{
    return $this->belongsTo(User::class);
}
public function consumption()
{
    return $this->hasMany(Consumption::class);
}
```

Figure 4.8: Household's Relations Examples

As shown, a household belongs to an user and each household has many consumptions, or at least can have many.

This approach allows intuitive queries, such as retrieving all households in a specific community:

```
$households = Community::find(1)->households;
```

Figure 4.9: Eloquent ability

Another important feature that Laravel provides is 'seeders'. Seeders are created to populate a table whenever it is needed for testing purposes. The following figure 4.10 illustrate the seeder of the default PV installations used to test the model, providing a faster way to insert recurring data.

```
class PVInstallationsTableSeeder extends Seeder
{
    public function run(): void
    {
        Log::info('Running PVInstallationsTableSeeder');
        DB::table('pv_installations')->insert([
            ['id' => 1, 'peak_power' => 3, 'pv_efficiency' => 0.90, 'dc_losses' => 0.05, 'dc_joule_losses' => 0.01,
             'inv_efficiency' => 0.99, 'ac_joule_losses' => 0.005],
        ]);
        DB::table('pv_installations')->insert([
            ['id' => 2, 'peak_power' => 3.5, 'pv_efficiency' => 0.92, 'dc_losses' => 0.05, 'dc_joule_losses' => 0.01,
             'inv_efficiency' => 0.99, 'ac_joule_losses' => 0.005],
        ]);
        DB::table('pv_installations')->insert([
            ['id' => 3, 'peak_power' => 4, 'pv_efficiency' => 0.94, 'dc_losses' => 0.05, 'dc_joule_losses' => 0.01,
             'inv_efficiency' => 0.99, 'ac_joule_losses' => 0.005],
        ]);
        DB::table('pv_installations')->insert([
            ['id' => 4, 'peak_power' => 2, 'pv_efficiency' => 0.96, 'dc_losses' => 0.05, 'dc_joule_losses' => 0.01,
             'inv_efficiency' => 0.99, 'ac_joule_losses' => 0.005],
        ]);
    }
}
```

Figure 4.10: Photovoltaic Installations Seeder

4.2 Weather API

APIs are an essential part of today's software systems, allowing smooth communication between various services and applications through Hypertext Transfer Protocol (HTTP). Within the framework of WattFuture, APIs are crucial in enabling the sharing of important information, such as weather data, that is necessary for precise energy forecasting and improvements.

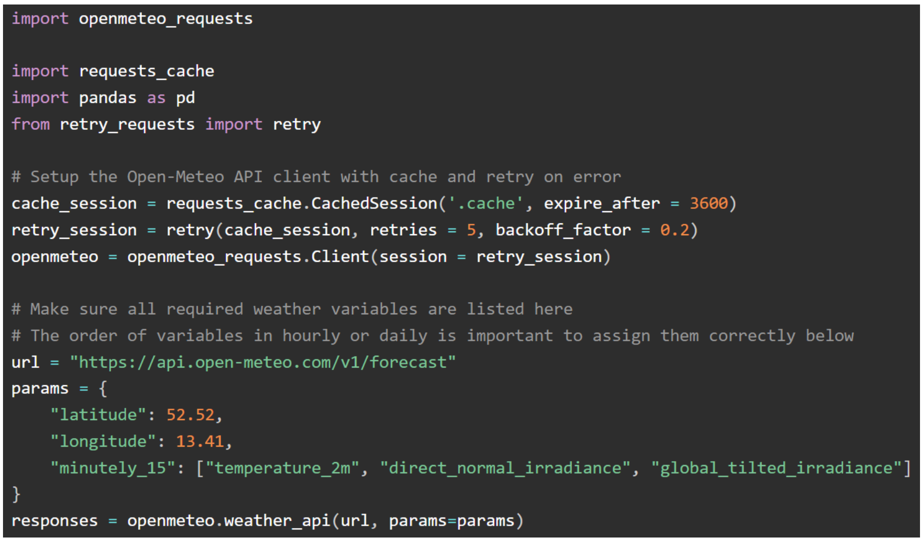
WattFuture relies heavily on weather data, such as temperature and solar radiation, to achieve its predictive modeling goals. The integration of external APIs allows the system to retrieve both historical and forecasted weather information, which is then used to inform various aspects of the project.

For the initial training of the predictive model, historical temperature data was required to establish accurate baseline predictions. An external API was utilized to gather this historical data, enabling the creation of a robust model that reflects real-world conditions.

Moreover, real-time weather forecasting is integral to the ongoing operation of WattFuture. The system continuously retrieves up-to-date temperature and radiation forecasts via API calls. This data is essential for calculating photovoltaic PV production, as it directly influences the system's energy source management and optimization processes.

WattFuture uses the Open-Meteo API, from Open-Meteo (2025) to gather historical weather data, which is crucial for predicting energy consumption patterns. By querying the API with specific latitude and longitude coordinates, we retrieve hourly temperature data for populating the baseline database. This data is then cross-referenced with energy consumption data to improve prediction accuracy. When dealing with PV predictions, WattFuture uses Open-Meteo API to retrieve temperature and irradiance data at 15 minutes intervals over the course of a week.

In the figure 4.11 it is possible to see an example, provided by Open-Meteo's website, of how the API calls works for a 15 minutely weather forecast.



```
import openmeteo_requests

import requests_cache
import pandas as pd
from retry_requests import retry

# Setup the Open-Meteo API client with cache and retry on error
cache_session = requests_cache.CachedSession('.cache', expire_after = 3600)
retry_session = retry(cache_session, retries = 5, backoff_factor = 0.2)
openmeteo = openmeteo_requests.Client(session = retry_session)

# Make sure all required weather variables are listed here
# The order of variables in hourly or daily is important to assign them correctly below
url = "https://api.open-meteo.com/v1/forecast"
params = {
    "latitude": 52.52,
    "longitude": 13.41,
    "minutely_15": ["temperature_2m", "direct_normal_irradiance", "global_tilted_irradiance"]
}
responses = openmeteo.weather_api(url, params=params)
```

Figure 4.11: Weather Forecast API Call

4.3 Predictive Model

Precise forecasts are essential for the efficiency of WattFuture, as they give the controller the required information to make well-informed choices. Selecting and implementing a strong predictive model is crucial in order to accomplish this.

The Python pandas library is essential in this process, providing a wide range of features for manipulating and analyzing data, which are crucial for working with predictive models.

At the initial stages of development, the Anaconda distribution was utilized to set up a controlled environment, with JupyterLab serving as the platform for testing various predictive models. These initial models were trained on a limited dataset, sufficient for establishing a baseline performance level. However, WattFuture is designed to continually refine its predictions by updating the model as more user-specific data becomes available. This adaptable method guarantees the model progresses over time by enhancing its precision and customizing its predictions to individual user profiles more effectively.

Identifying the best predictive model is difficult due to the variety of potential use cases, making testing necessary. Different types of predictive models can differ greatly, ranging from basic linear regression to more advanced techniques such as decision trees, support vector machines, artificial neural networks, and ensemble methods like random forests and gradient boosting machines. Choosing the right model relies on the unique attributes of the data and the specific issue being addressed.

Building a high-performance predictive model is a structured and iterative procedure, every step is critical to the end result. Shin et al. (2024) point out that preprocessing, in itself, significantly improves model accuracy, by optimizing data patterns prior to prediction. There are four phases to build a predictive model:

- **Pre-processing** - This initial phase focuses on data collection, cleaning, and formatting to ensure that only high-quality and consistent information is used for training. Handling missing values, filtering anomalies, and preparing relevant features are essential tasks at this stage.

- **Model Selection** - Based on the nature of the data and the prediction objectives, an appropriate algorithm must be selected.

- **Model Training** - In this phase, the selected model is trained using the prepared dataset. The goal is to enable the model to learn patterns and relationships within the data that can be generalized to future predictions.

- **Metrics Evaluation** - Once the model is trained, its performance must be assessed using appropriate evaluation metrics. This step ensures that the model's predictions are accurate and reliable

The following figure 4.12 illustrates the inputs needed for the predictive model and the expected output.

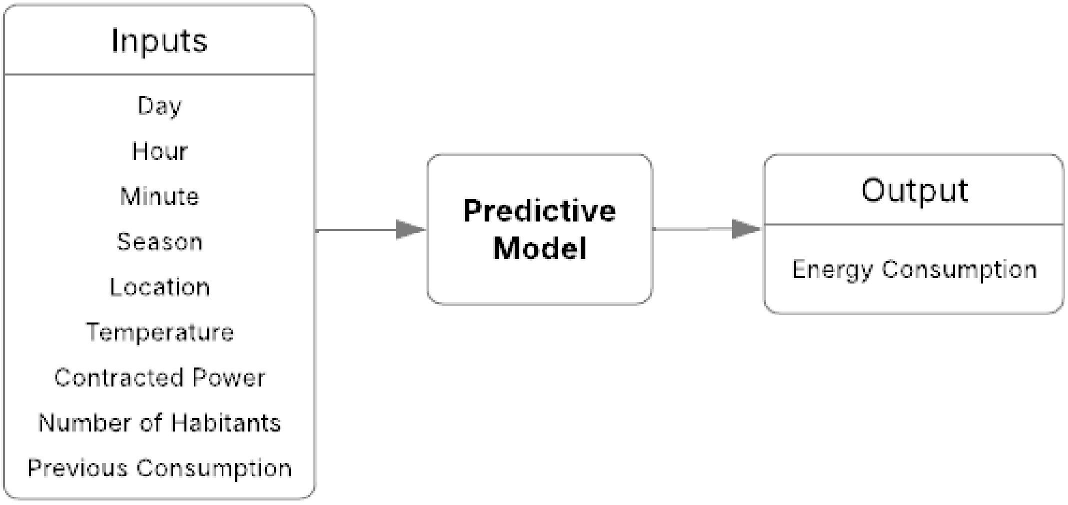


Figure 4.12: Predictive Model Diagram

4.3.1 Data Collection

To ensure that the WattFuture predictive model was based on realistic and accurate data, real energy consumption data was collected. Acquiring actual consumption data is often challenging due to the need for restricted access to personal information. However, through collaboration with friends and family members, WattFuture was able to gather a sufficient dataset to train the initial version of the predictive model. With intelligent counters, E-Redes provides a website page for the consumer to keep track of their consumptions, with the ability to download excel files with 15 minutely database as shown in figure 4.13.

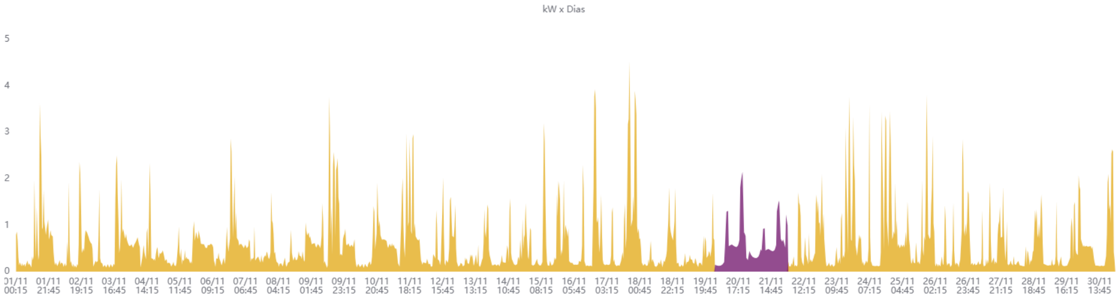


Figure 4.13: E-REDES Historical Power Consumption Example

This information is crucial for the early stages of WattFuture but the main idea is to collect all the consumption information directly from the energy smart meter, in the same format provided by the E-Redes website.

Given the limited scope of available personal data, since energy consumption data from E-Redes is private, WattFuture's initial database is restricted, which may affect the model's predictive accuracy due to a lack of data to train the model. Despite these limitations, the predictive model developed by WattFuture has demonstrated promising results at this early stage. This initial performance is not a major concern, as the model is designed to be continuously updated. As more data is collected and integrated, the model's predictive accuracy and efficiency are expected to improve over time, particularly as it learns from each household personal behavior.

To achieve these results, WattFuture collected and utilized several key pieces of information, including:

1. **Date** - Knowing the date is important for figuring out the day of the week, which is necessary for analyzing consumption patterns linked to everyday habits. For instance, usual workweek schedules from Monday through Friday commonly lead to decreased use of electricity at home on these days, whereas weekends might exhibit varied patterns. Also, the presence of dates assists in recognizing seasonal trends, which can have a substantial impact on energy consumption.

2. **Time** - Data was gathered every 15 minutes to precisely record changes in energy consumption, identify seasonal patterns, and synchronize with tariff schedules. This detailed time information is crucial for analyzing how consumption trends vary during different times of the day and for efficiently managing energy use during peak and off-peak times.

3. **Weather** - The weather directly affects energy usage since extreme conditions lead to increased usage of heating and cooling systems. By integrating weather information, the model can modify its forecasts with the help of outside temperature and solar irradiance, enhancing precision.

4. **Habitants** - The number of people living in a household has a big impact on how much energy is used. In general, more occupants lead to higher energy consumption. This data enables the model to make more accurate predictions regarding household size.

5. **Location** - Geographic location plays a role in regional energy consumption patterns due to differences in climate, household sizes, and energy usage habits. Adding geographical information improves the model's capacity to forecast energy consumption in diverse regions.

Date and time variables are an input from E-Redes files, weather variable comes from Open-Meteo API, habitants and location variables are defined by the user.

4.3.2 Data Preparation

The foundation of a predictive model is a reliable and high quality dataset. A considerable amount of useful and relevant data is crucial for the model's reliability and accuracy. Starting by gathering the most consumption data available from friends and family.

This diverse dataset provided a comprehensive starting point for the creation of a script designed to process, clean, and enrich the data.

A python script was developed to read Excel files containing consumption data and extract relevant attributes, such as date, time, and energy consumption. The remaining variables (habitants and location) are an input from the user himself. The script primary goal is to systematically process the data and store valid entries in a structured format, specifically a data frame, which serves as the basis for analysis and modeling.

To ensure the reliability and integrity of the dataset:

- **Real vs Estimated Values** - The script was programmed to identify and exclude estimated values often present in the Excel files. By focusing only on actual measured data, the veracity of the dataset was significantly enhanced.
- **Anomaly Detection** - The script incorporates functionality to detect and discard unusual consumption values that deviate significantly from expected ranges. This step prevents outliers or erroneous entries from skewing the results and ensures the dataset accurately represents typical consumption patterns.

Beyond consumption data, the script was designed to enrich the dataset by incorporating weather information. For each consumption entry, the script retrieves corresponding weather data, such as temperature, through an API.

This additional layer of information is critical, as temperature and other environmental factors are known to influence energy consumption patterns. For example, weather conditions often implies the use of heaters during winter or fans during summer.

By systematically integrating weather data, the model's accuracy will improve, allowing it to account for seasonal and environmental variations in energy consumption.

4.3.3 Predictive Models

After cleaning all the data and getting the final data frame, it is now possible to define input feature, target variables and split the data into training and testing sets. For the record, a 80/20 was used to train the predictive model, this means that 80% of the data is known and 20% will be predicted and then compared with the real one to get the results.

Multiple predictive models were experimented with to determine the most appropriate one for this project. Here is a list of the top models that were assessed:

1. **ANN** - ANN is a computational model that takes inspiration from the neural networks present in the human brain. Artificial Neural Networks can identify intricate patterns in data by utilizing interconnected layers of nodes like neurons. They excel at representing non-linear connections and are commonly applied in tasks related to time series prediction and pattern recognition.
2. **K-Nearest Neighbors Algorithm (K-NN)** - K-NN is an uncomplicated algorithm for learning which categorizes data points by their distance to the 'k' closest neighbors

in the feature space. In regression tasks, it forecasts the value of a new data point by taking the average of its closest neighbors' values. Implementing K-NN is simple and can be efficient for datasets of small to medium sizes.

3. **LightGBM Regressor** - It is a gradient boosting framework created by Microsoft, aimed at being extremely efficient and scalable. LightGBM is highly effective at managing extensive datasets with high dimensionality. It constructs numerous decision trees sequentially, optimizing them to reduce the prediction error. It is especially successful for tasks that demand high levels of prediction precision and quickness.

4. **Histogram Gradient Regressor** - It is a modified version of conventional gradient boosting techniques which employs histograms to estimate the distribution of continuous attributes. This method greatly decreases the amount of time spent on calculations and the use of memory, making it appropriate for handling big data sets. It strikes a balance between the complexity of the model and its efficiency.

5. **XGBoost Regressor** - It is a sophisticated version of gradient boosting created for fast and efficient performance. XGBoost comes with capabilities like regularization for preventing overfitting and parallel processing for efficiently managing large datasets. It is renowned for its precision and has gained popularity in numerous machine learning contests.

6. **Random Forest Regressor** - It is a technique in ensemble learning that constructs numerous decision trees and combines their outputs for a more precise and reliable prediction. By taking the average of individual tree results, variance is minimized and generalization is enhanced. Random Forest is resistant to overfitting and is suitable for both classification and regression assignments.

To objectively compare different models, several key metrics are commonly used. These metrics provide quantitative measures to evaluate model performance.

1. **Coefficient of Determination** - Known as R^2, evaluates the percentage of variability in the dependent variable that can be explained by the independent variables. It varies from 0 to 1, with 0 meaning the model doesn't account for any variance, and 1 meaning it accounts for all variance in the data. A greater R^2 value typically indicates a stronger alignment between the model and the data.

2. **Mean Squared Error (MSE)** - MSE measures the average squared discrepancy between the predicted and true values. MSE is highly affected by outliers as it squares errors, magnifying bigger differences. Smaller MSE values suggest superior model performance.

3. **Root Mean Squared Error (RMSE)** - RMSE is the square root of MSE and indicates the deviation of the prediction errors. It is measured in equivalent units as the dependent variable, which renders it more understandable than MSE. A decreased RMSE shows that predictions are more precise.

4. **Mean Absolute Error (MAE)** - MAE quantifies the mean absolute discrepancy between anticipated and actual outcomes. Different from MSE, MAE doesn't square the errors, giving equal weight to all errors and not penalizing larger errors more. A smaller MAE suggests a more accurate model.

Using these measurements helps in making informed choices about selecting and improving predictive models, ensuring that WattFuture provides reliable and precise predictions tailored to individual user profiles.

4.3.4 Predictive Models Selection

As mentioned earlier, WattFuture uses a predictive model to forecast consumption values based on each individual user. However, it is necessary to have an initial baseline so that the model has some values to base itself on. That said, WattFuture is not expected to have a perfect system from the start, as the model is not yet prepared for each specific customer, resulting in good results, but not excellent ones.

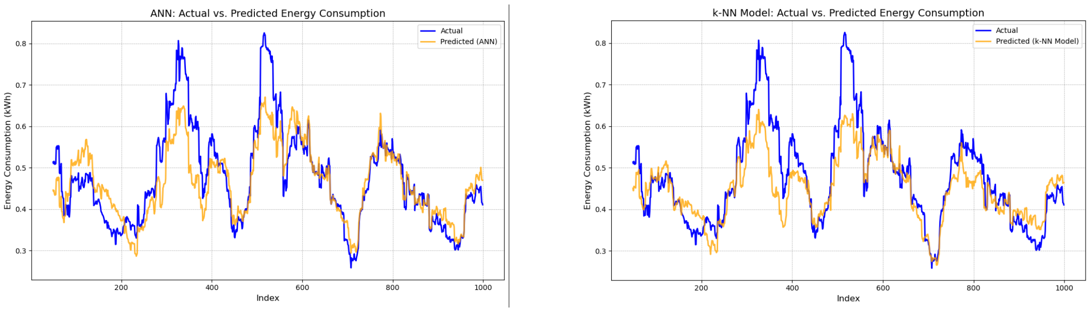
As illustrated in Table 4.1, the primary predictive models evaluated during the development of WattFuture are presented, along with their associated evaluation metrics.

Table 4.1: Predictive Models Tested

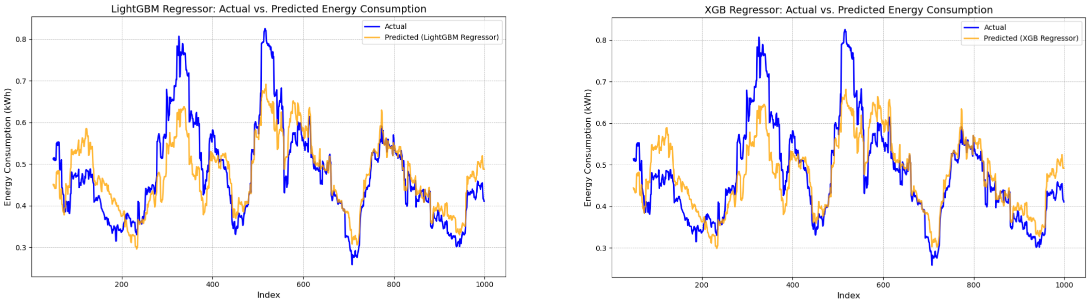
Model Name	**MSE**	**RMSE**	**Coefficient of Determination**	**MAE**
ANN	0.1009	0.3176	0.7008	0.1456
K-NN	0.1372	0.3704	0.5908	0.1948
LightGBM Regressor	0.0994	0.3153	0.7034	0.1447
Histogram Gradient Regressor	0.0999	0.3161	0.7021	0.1447
XGBoost Regressor	0.0998	0.3160	0.7022	0.1450
Random Forest Regressor	0.1081	0.3288	0.6776	0.1570

For a graphical perspective, the following graphs were created to represent the best models tested:

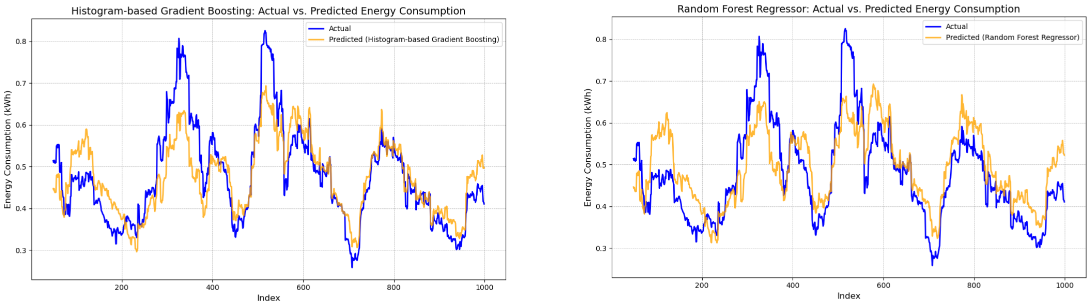
It is evident from the graphs in figure 4.14 that several models are suitable for the WattFuture objective, as several models have obtained positive and competitive results. Four models stand out as being particularly competitive: the Artificial Neural Network (graph ′a′), the LightGBM Regressor (graph ′c′), the XGBoost Regressor (graph ′d′) and the Histogram-based Gradient Boosting (graph ′e′). Table 4.1 shows that the LightGBM regressor showed the best overall performance based on MSE and RMSE. However, other



(a) ANN Model (b) k-NN Model



(c) LightGBM Regressor (d) XGBoost Regressor



(e) Histogram-based Gradient Boosting (f) Random Forest Regressor

Figure 4.14: Performance of Different Predictive Models

models such as XGBoost and ANN also achieved comparable results, making them strong alternatives.

However, despite the apparent superiority of these models, the decision was taken to employ the ANN model in WattFuture, a choice that was informed by several factors:

- **Adaptability** - As discussed in section 4.3.3, ANN models have the ability to identify complex patterns and non-linear relationships, which makes it susceptible to learning more patterns and improving as datasets increase.

- **Flexibility** - These results are based of a limited dataset which can benefit other models that would underperform in larger datasets. ANN should not struggle to maintain its accuracy when the complexity of the dataset grows.

This choice is aimed at long-term adaptability rather than immediate performance gains. Even thought ANN was chosen to be WattFuture's model, it's important to remember that models such as LightGBM and XGBoost should be retested at a later stage when more data is available to ascertain the validity of this assumption.

4.4 PV Production Forecast

In addition to forecasting consumption, the python script also forecasts photovoltaic energy production using the temperature and irradiance provided by the weather API. Assuming the following default variables:

- Nominal Operating Cell Temperature (NOCT) = 46 degrees Celsius.
- `T_NOCT` (Ambient Temperature at NOCT)= 20 degrees Celsius.
- `G_NOCT` (Nominal Irradiance for NOCT) = 800 W/m^2.
- alpha (Temperature Coefficient of Power) = -0.004 per degree Celsius.

To calculate the energy production we need to know the cell temperature (T_{cell}), given by the following formula:

$$T_{\text{cell}} = T_{\text{amb}} + \frac{\text{NOCT} - T_{\text{NOCT}}}{G_{\text{NOCT}}} \cdot G_{\text{DNI}} \tag{4.1}$$

T_{amb} represents the ambient temperature at the time and G_{DNI} represents the direct normal irradiance. These variables are obtained by the weather API.

The next step is to calculate the maximum power that the PV panel could produce with the previous T_{cell} at Standard Test Conditions (STC). This maximum power(P_{max}) depends on the installation peak power (P_{peak}), the global tilted irradiance (G_{tilted}) and the PV efficiency (η_{PV}).

$$P_{\text{max}} = P_{\text{peak}} \cdot \frac{G_{\text{tilted}}}{1000} \cdot \eta_{\text{PV}} \tag{4.2}$$

The actual Direct Current (DC) power produced (P_{DC}) by the PV panel depends on the temperature conditions and the temperature coefficient of power (α)

$$P_{\text{DC}} = P_{\text{max}} \cdot (1 + \alpha \cdot (T_{\text{cell}} - 25)) \tag{4.3}$$

The energy produced needs to be converted to Alternating Current (AC) power with an inverter but there are some losses such as general DC losses (degradation, shading, etc.), represented by Loss_{DC} and resistive losses ($\text{Loss}_{\text{Joule,DC}}$) caused by the resistant in cables and components.

$$P_{\text{DC,inv}} = P_{\text{DC}} \cdot (1 - \text{Loss}_{\text{DC}}) \cdot (1 - \text{Loss}_{\text{Joule,DC}}) \tag{4.4}$$

Then, the conversion to AC power has inefficiencies depending on the inverter's efficiency(η_{inv}). This inefficiency results in the following AC power, $P_{\text{AC,inv}}$.

$$P_{\text{AC,inv}} = P_{\text{DC,inv}} \cdot \eta_{\text{inv}} \tag{4.5}$$

The final power produced ($P_{\text{production}}$) is calculated by subtracting the AC losses ($\text{Loss}_{\text{Joule,AC}}$) from the previous $P_{\text{AC,inv}}$.

$$P_{\text{production}} = P_{\text{AC,inv}} \cdot (1 - \text{Loss}_{\text{Joule,AC}}) \tag{4.6}$$

4.5 PuLP Model

After the script is successfully complete, a data frame with all the essential information is created and stored in the database as table "Predictions". This table brings together production and consumption forecasts, ready to be analyzed in order to identify the best energy sources.

Managing energy consumption and production effectively in dynamic and personalized scenarios requires a robust optimization framework. While rule-based systems offer a basic approach, they lack the flexibility to adapt to unique household behaviors or varying conditions. To address this, a linear programming optimization model using the PuLP library was developed. This model evaluates multiple scenarios and determines the optimal energy source allocation to minimize costs while meeting energy demands.

4.5.1 Variables and Target

The PuLP model defines several decision variables, LPVariables, that WattFuture uses to represent key energy flow components and battery operations. These variables serve as the basis for optimization.

The primary decision variables used in the model include:

- **Grid Use** - Energy drawn from the grid.
- **PV Use** - Energy used directly from PV production.
- **Battery Use** - Energy discharged from the battery to meet demand.
- **Battery Charge** - Total energy charged into the battery.
- **Charge by Grid** - Energy charged into the battery from the grid.
- **Charge by PV** - Energy charged into the battery from PV production.
- **Battery SoC** - Battery state of charge at each interval.

Binary variables were also employed to ensure mutually exclusive actions for the battery, such as:

- **Battery Charging** - Indicates if the battery is charging during a specific time interval.
- **Battery Discharging** - Indicates if the battery is discharging during a specific time interval.

The objective of the PuLP model is to minimize the total energy cost for the household or community. This is expressed as:

$$\text{total\_cost} = \sum_{i} (\text{grid\_use}[i] + \text{charge\_by\_grid}[i]) \times \text{price}[i] \tag{4.7}$$

With 'i' representing the amount of entries in the data frame. This function calculates the cost of energy sourced from the grid, including energy used directly for consumption and energy stored in the battery.

It is important to notice that the total cost is directly related with electricity tariffs, represented by price[i], making them highly impactful to PuLP's model performance. If the price doesn't fluctuate throughout the day, there is no benefit in using the grid to charge the battery.

4.5.2 Constraints

Instead of only using rules to solve the problem, this model uses constraints that allow flexibility to the model if programmed properly. To guide the optimization process and ensure feasible solutions, the following table 4.2 show the main constraints that were implemented:

Table 4.2: PuLP Constraints

Constraint	**Description**
Energy Consumption	The sum of energy sources (*grid use* + *PV use* + *battery use*) must meet total energy consumption.
Valid Values	Energy source variables (*grid use*, *PV use*, *battery use*) must be non-negative.
PV Production	PV energy used cannot exceed PV production energy prod energy prod.
Battery State	The battery can't be charging and discharging at the same time.
Battery Charge Rate	When the battery is charging it can't pass its limitation, its charging rate.
Battery Discharge Rate	When the battery is discharging it can't pass its limitation, its discharging rate.
Charge by PV	The model must limit the the battery charging by PV variable to the energy production available minus the PV Usage.

4.5.3 Implementation

The PuLP model is integrated into the WattFuture system via Python, where it interacts with household or community specific data stored in the database. The model processes predictions of energy consumption and production, weather data, and electricity pricing. Once the optimization is complete, it outputs:

- The optimal usage of energy sources for each time interval.
- The resulting battery state of charge and grid usage.
- The overall cost and energy savings achieved.

The outputs are then stored in the energy sources table and visualized on the user interface for transparency and decision-making.

Unlike static rule-based systems, the PuLP model leverages constraints to adapt to dynamic behaviors. For example:

A household uses more energy during the hours of 2pm and 6pm, which is neither a high peak nor a low peak, and doesn't use as much during peak hours. Saving the battery for peak hours using rules won't be as efficient as saving it for peak energy consumption hours, even if it is not the highest price of the day.

This adaptability ensures that the system can accommodate diverse household energy profiles and respond to varying environmental and pricing conditions.

By combining predictive modeling with linear programming, the PuLP model offers a scalable, flexible, and cost-effective approach to managing energy consumption and storage. Its ability to evaluate complex scenarios and make optimal decisions demonstrates the potential of optimization in modern energy systems. Through the integration of constraints and objective-driven modeling, the system not only adapts to user-specific behaviors but also ensures efficient energy utilization, reducing overall costs and maximizing PV production benefits.

4.6 Framework

An organized structure is essential for the success of this project, as it acts as the system's foundation. Laravel was chosen for this project because of its strong features and its appropriateness for web development. Furthermore, my previous familiarity with Laravel led me to consider it a suitable and calculated decision for this project.

Laravel is a Hypertext Preprocessor (PHP)-powered, freely available framework built to help create durable and easily-manageable web applications. Laravel (2025) Renowned for its graceful structure, segmented layout, and extensive range of functions, Laravel is especially fitting for endeavors that demand scalability, security, and quick progress.

4.6.1 Laravel Overview

Laravel is an Model-View-Controller (MVC) framework that equips developers with the tools and structures needed to efficiently create modern web applications. The reason for its popularity is its capability to streamline everyday tasks like routing, authentication, session management, and caching, which are essential for the majority of web applications.

Some of Laravel's characteristics consist of:

1. **Eloquent ORM** - Laravel's native ORM system, Eloquent, offers a straightforward way to work with databases through a simple ActiveRecord implementation. Eloquent simplifies handling database connections and executing intricate searches.
2. **Blade Templating Engine** - Blade is a simple templating engine in Laravel that enables developers to create dynamic interfaces easily. Blade allows for a distinct division between logic and presentation, allowing for components to be reused in various views.
3. **Routing system** - Laravel's routing system provides a simple way to define web routes. It provides various routing possibilities, such as closures, controller methods, and resource routing, necessary for managing HTTP requests and responses.
4. **Middleware** - Middleware in Laravel provides a way to examine and filter incoming HTTP requests to the application. Middleware is crucial for incorporating features like authentication, logging, and managing Cross-Origin Resource Sharing (CORS).
5. **Artisan Console** - The Command Line Interface (CLI) of Laravel, offers a variety of tools for executing repetitive tasks like database migrations, seeding, and generating boilerplate code.

4.6.2 Laravel Project Structure

The layout of a Laravel project is designed to encourage the segregation of responsibilities, facilitating the development, testing, and upkeep of the application. The main elements of the Laravel project consist of:

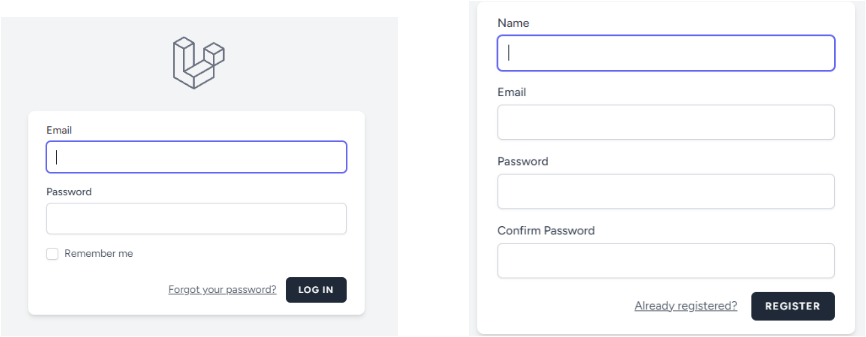
1. **Application Directory** - Within this directory, you can find the fundamental code of the app such as models, controllers, and middleware. The MVC pattern is evident in this setup, with subdirectories for Models, Views, and Controllers.
2. **Routes Directory** - Directory with all route definitions, mapping Uniform Resource Locator (URL)s to controller actions or closure functions. The web.php file manages web routes, while api.php manages routes for API endpoints.
3. **Resources Directory** - The Blade templates, found in the resources directory, are used to create dynamic content for the user interface. It also holds localization files

and raw asset files, like JavaScript and CSS, that are compiled and incorporated into views.

4. **Database Directory** - Within this directory are migration files, factories, and seeders that define and populate the database schema.

4.6.3 Laravel Website

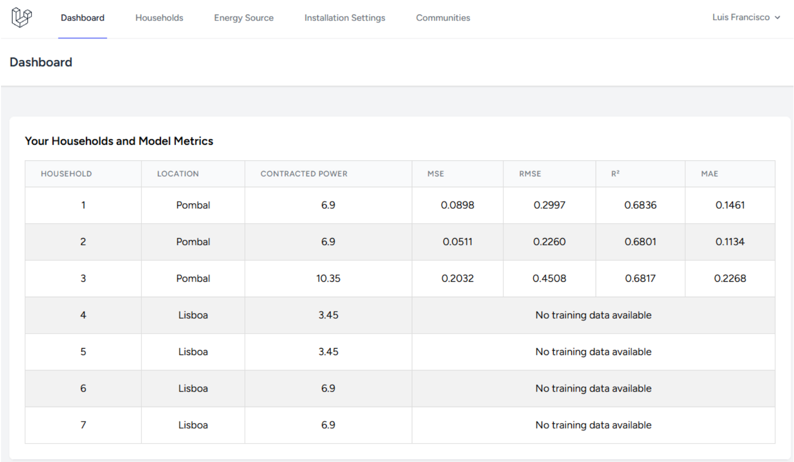
The Laravel Breeze package was used to provide a simple and intuitive starting point for user authentication. Breeze offers basic functionality for login, registration, password reset, email verification, and profile management.



(a) Log In page (b) Register page

Figure 4.15: Breeze's user authentication system

Figure 4.15a and figure 4.15b demonstrate Breeze's login and registration pages. Upon successful login, users are directed to a dashboard page, which provides an overview of the system's evaluation metrics. This dashboard enables users to assess the performance of the predictive models and identify whether a personalized model is being used for each household or if the default model remains active. Figure 4.16 displays the dashboard page, where it is evident that households with sufficient historical data have transitioned to personalized models, while others continue to rely on the default.



Dashboard

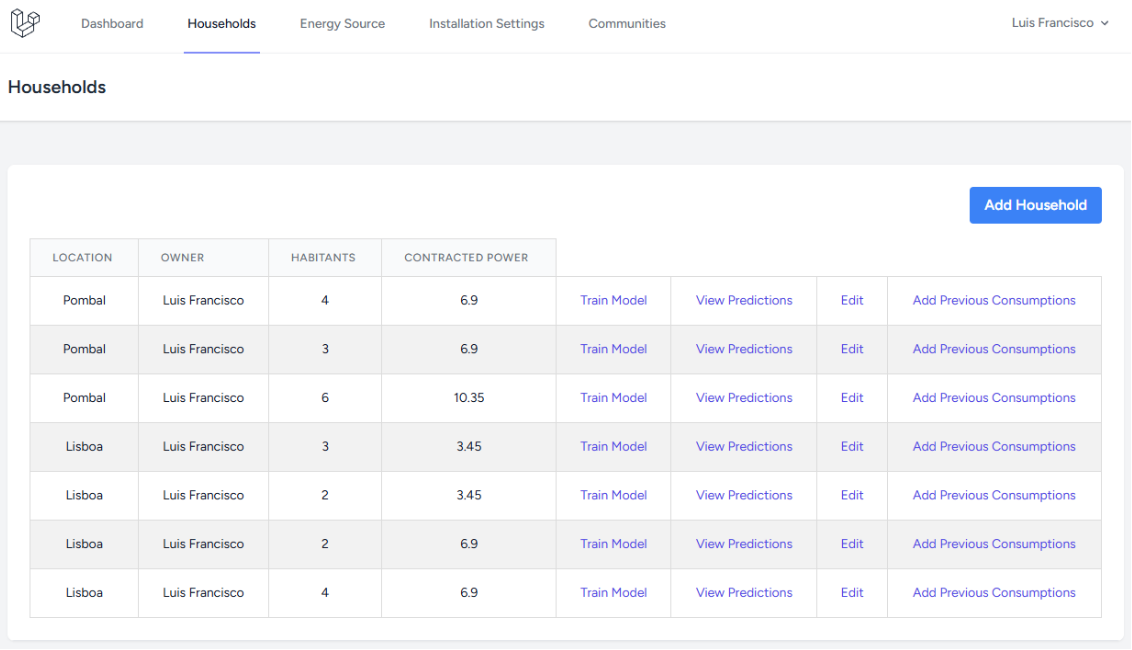
Your Households and Model Metrics

HOUSEHOLD	LOCATION	CONTRACTED POWER	MSE	RMSE	R^2	MAE
1	Pombal	6.9	0.0898	0.2997	0.6836	0.1461
2	Pombal	6.9	0.0511	0.2260	0.6801	0.1134
3	Pombal	10.35	0.2032	0.4508	0.6817	0.2268
4	Lisboa	3.45	No training data available			
5	Lisboa	3.45	No training data available			
6	Lisboa	6.9	No training data available			
7	Lisboa	6.9	No training data available			

Figure 4.16: Dashboard page

In cases where no households are registered, the dashboard will not display any model-related information. To address this, users can navigate to the Households page, illustrated in figure 4.17, where they can add new households and configure their properties.

- **Train Models** - Users can train individual household models, and if the evaluation metrics outperform the previous version, the system automatically updates the model.
- **View Predictions** - Provides access to future energy consumption predictions.
- **Edit Household Properties** - Users can modify details such as contracted power or tariff rates.
- **Add Previous Consumptions** - Users can upload historical consumption data via specific files to enrich the training dataset.



LOCATION	OWNER	HABITANTS	CONTRACTED POWER				
Pombal	Luis Francisco	4	6.9	Train Model	View Predictions	Edit	Add Previous Consumptions
Pombal	Luis Francisco	3	6.9	Train Model	View Predictions	Edit	Add Previous Consumptions
Pombal	Luis Francisco	6	10.35	Train Model	View Predictions	Edit	Add Previous Consumptions
Lisboa	Luis Francisco	3	3.45	Train Model	View Predictions	Edit	Add Previous Consumptions
Lisboa	Luis Francisco	2	3.45	Train Model	View Predictions	Edit	Add Previous Consumptions
Lisboa	Luis Francisco	2	6.9	Train Model	View Predictions	Edit	Add Previous Consumptions
Lisboa	Luis Francisco	4	6.9	Train Model	View Predictions	Edit	Add Previous Consumptions

Figure 4.17: Households page

By pressing the 'Add Household' button, users are directed to a new form, illustrated in figure 4.18, to input the necessary household details. This form captures all essential information required to integrate a new household into the system.

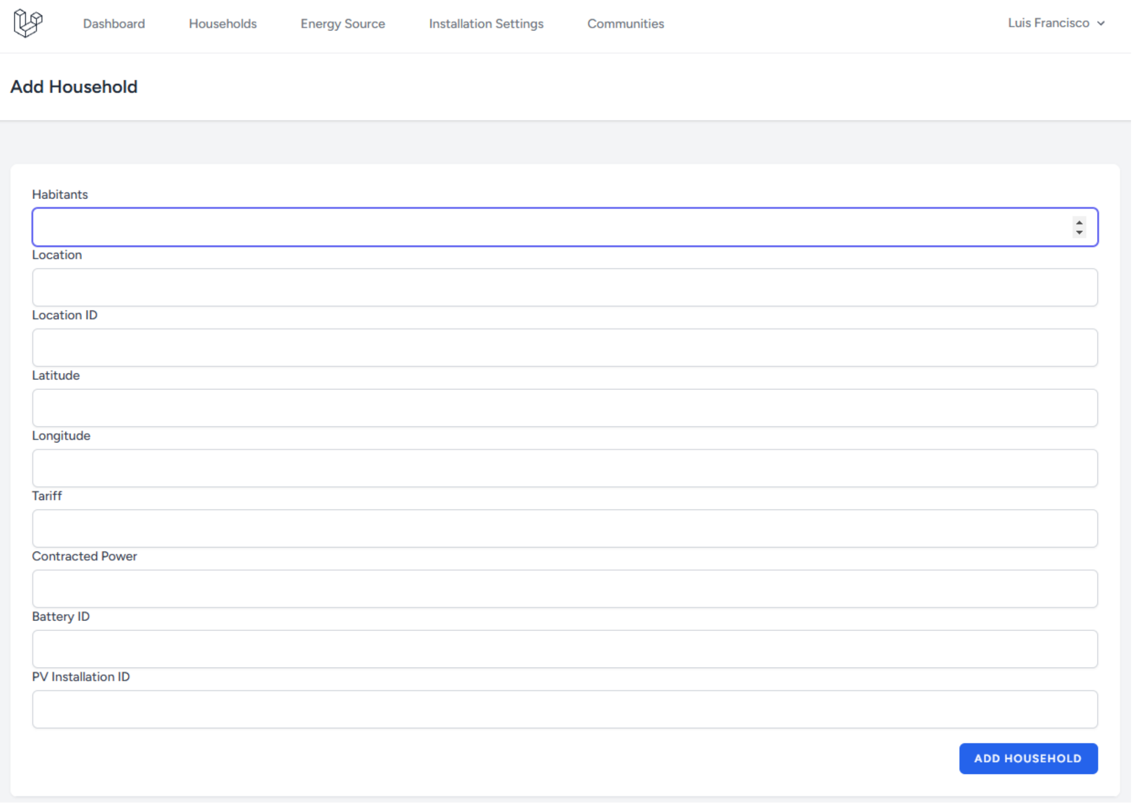
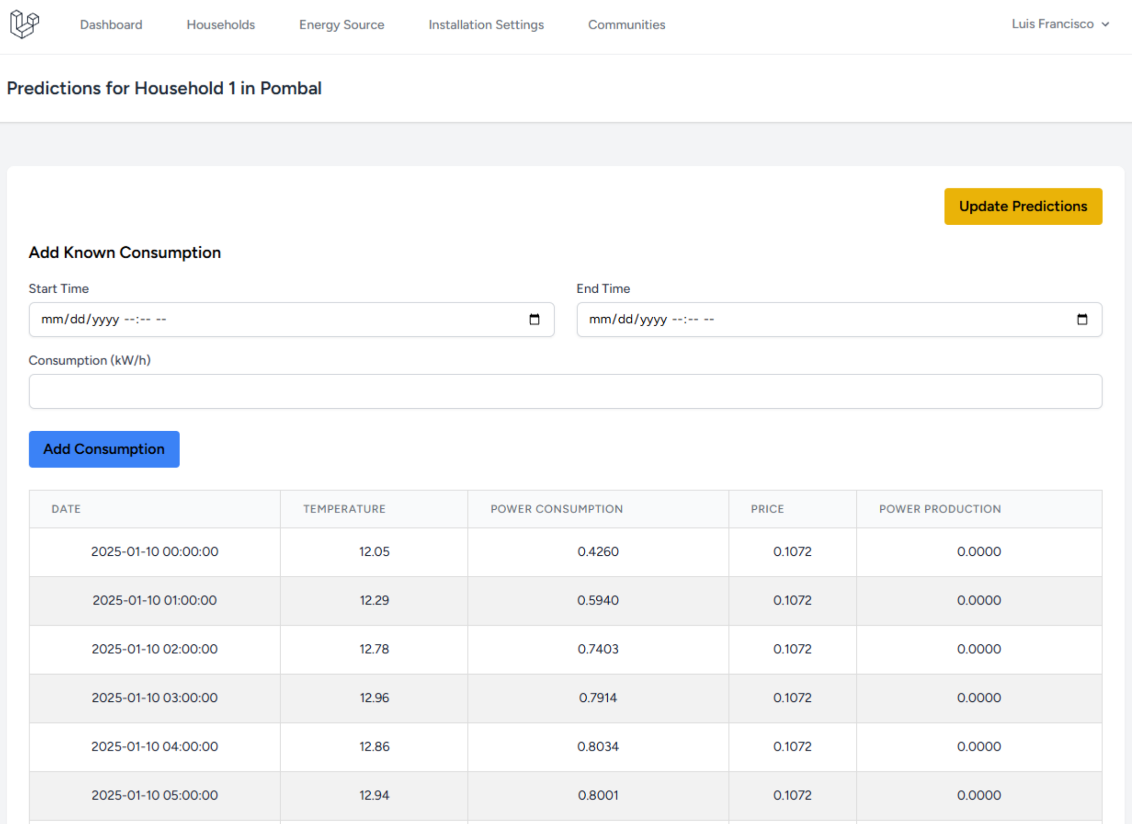


Figure 4.18: Add Household page

Additionally, selecting the 'View Predictions' button on the Households page redirects users to a new view where a detailed table of future energy values is displayed. As shown in figure 4.19, this table includes hourly predictions for temperature, price, power consumption and production, along with the capability to manually add known consumptions for more accurate forecasting.

Once predictions are generated, users can proceed to create an energy management plan for each household. This plan is presented in two formats:

1. Table View : A structured representation of energy allocations, figure 4.20.
2. Graphical View : A visual representation of energy distribution and management strategies, figure 4.21.



Predictions for Household 1 in Pombal

Add Known Consumption

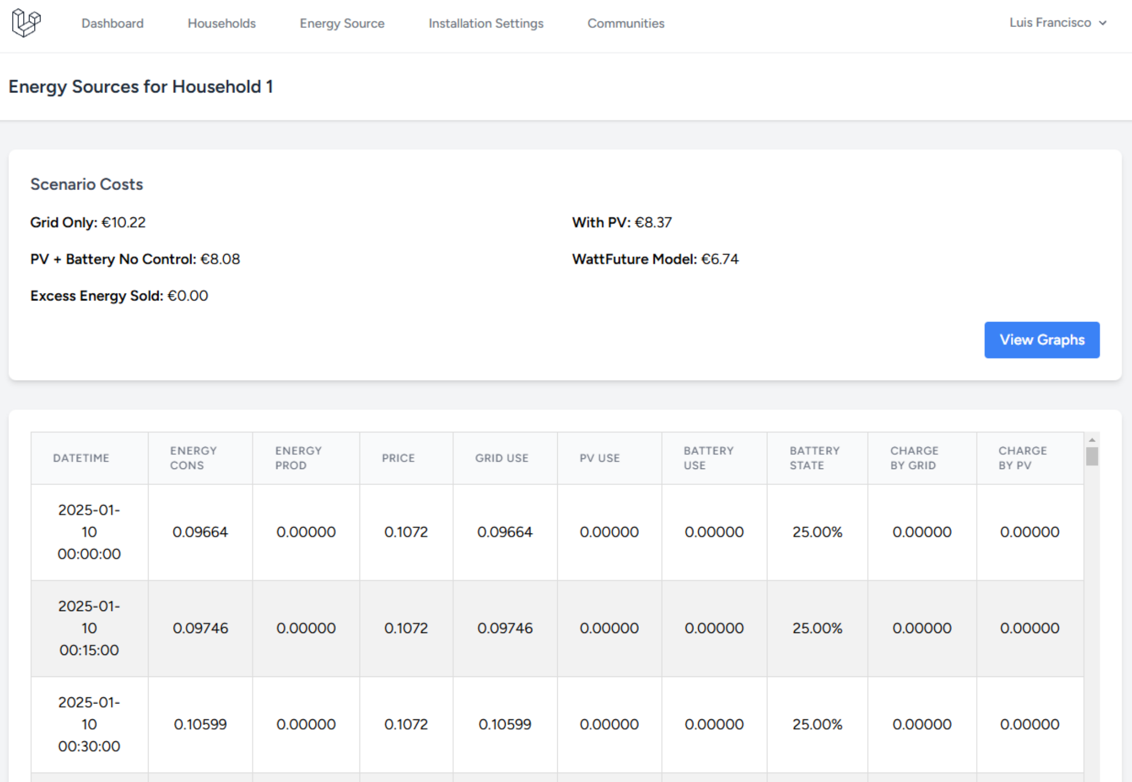
Start Time: mm/dd/yyyy --:-- --

End Time: mm/dd/yyyy --:-- --

Consumption (kW/h)

DATE	TEMPERATURE	POWER CONSUMPTION	PRICE	POWER PRODUCTION
2025-01-10 00:00:00	12.05	0.4260	0.1072	0.0000
2025-01-10 01:00:00	12.29	0.5940	0.1072	0.0000
2025-01-10 02:00:00	12.78	0.7403	0.1072	0.0000
2025-01-10 03:00:00	12.96	0.7914	0.1072	0.0000
2025-01-10 04:00:00	12.86	0.8034	0.1072	0.0000
2025-01-10 05:00:00	12.94	0.8001	0.1072	0.0000

Figure 4.19: Energy Predictions



Energy Sources for Household 1

Scenario Costs

Grid Only: €10.22

With PV: €8.37

PV + Battery No Control: €8.08

WattFuture Model: €6.74

Excess Energy Sold: €0.00

DATETIME	ENERGY CONS	ENERGY PROD	PRICE	GRID USE	PV USE	BATTERY USE	BATTERY STATE	CHARGE BY GRID	CHARGE BY PV
2025-01-10 00:00:00	0.09664	0.00000	0.1072	0.09664	0.00000	0.00000	25.00%	0.00000	0.00000
2025-01-10 00:15:00	0.09746	0.00000	0.1072	0.09746	0.00000	0.00000	25.00%	0.00000	0.00000
2025-01-10 00:30:00	0.10599	0.00000	0.1072	0.10599	0.00000	0.00000	25.00%	0.00000	0.00000

Figure 4.20: Energy Source page

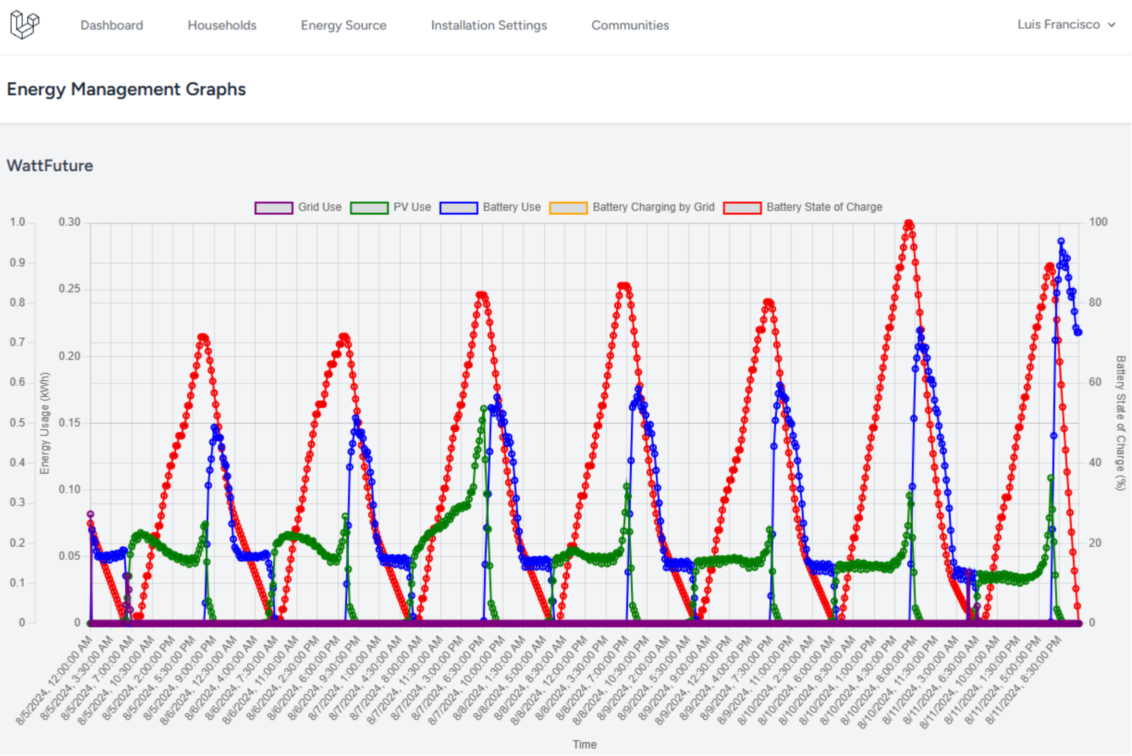


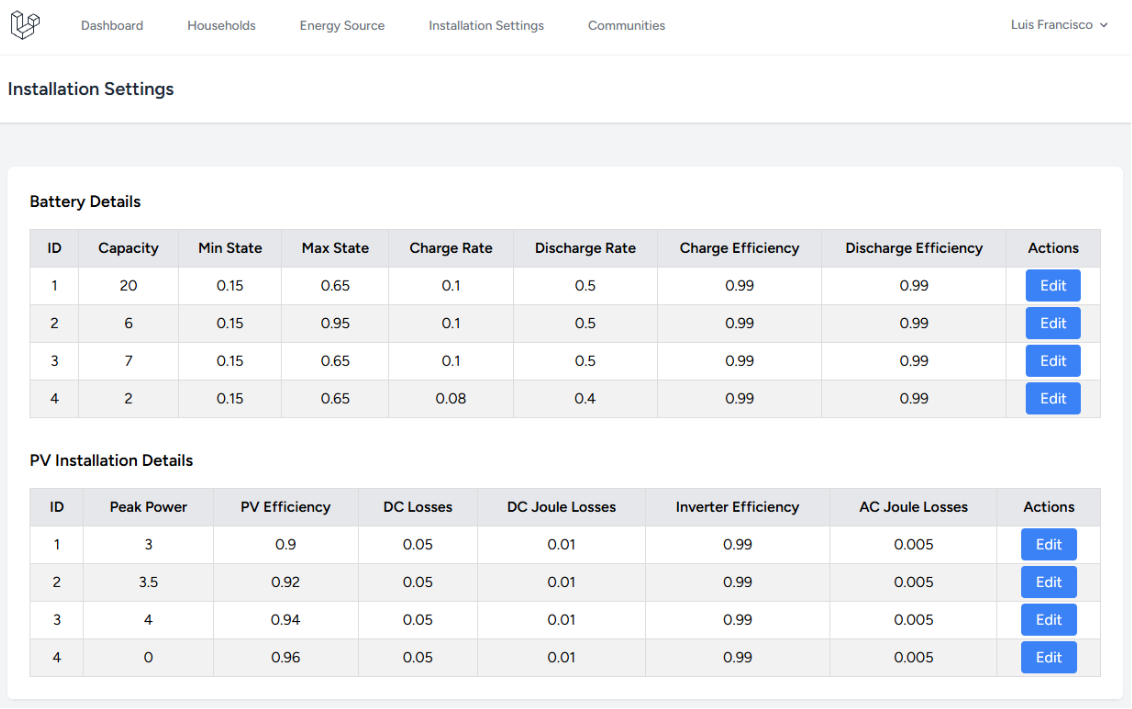
Figure 4.21: Energy Management Graphs page

The Energy Management Graphs page also includes three additional graphs, representing the scenarios discussed in chapter 3, section 3.3. These graphs allow users to analyze the energy management strategy for different configurations, such as grid-only usage, PV integration, and battery-enhanced optimization.

Being an administrator provides access to the Installation Settings page, where users can modify battery specifications and PV panel details. This page includes two tables listing all batteries and PV installations associated with the user. While, for testing purposes, all variables are currently editable, the intention is to restrict users to only modifying the minimum and maximum battery state. Other variables, such as charge/discharge rates and efficiency, will require adjustments by a qualified professional.

Figure 4.22 illustrates an example of the Installation Settings page.

Similar to the 'Households' page there is a 'Communities' page that display every community the user is part of, since it might have multiple households in different regions. Figure 4.23 shows a simple example of the 'Communities' page, where the user already has an existing community.



Installation Settings

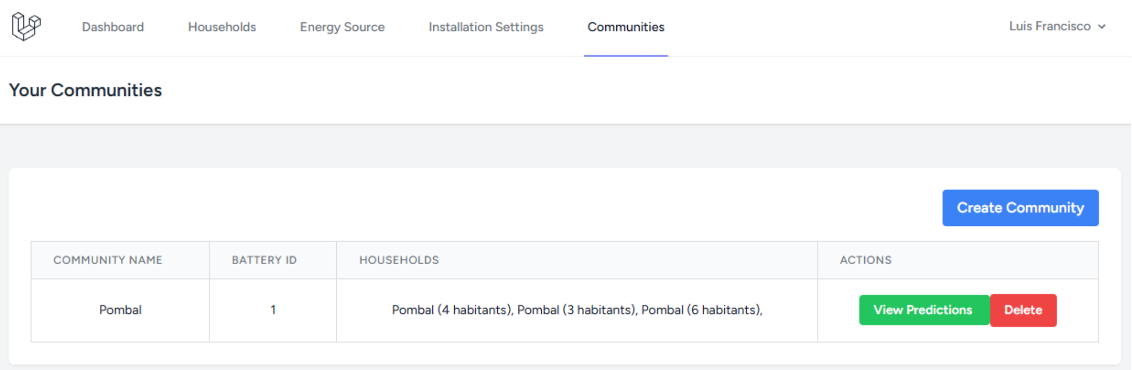
Battery Details

ID	Capacity	Min State	Max State	Charge Rate	Discharge Rate	Charge Efficiency	Discharge Efficiency	Actions
1	20	0.15	0.65	0.1	0.5	0.99	0.99	Edit
2	6	0.15	0.95	0.1	0.5	0.99	0.99	Edit
3	7	0.15	0.65	0.1	0.5	0.99	0.99	Edit
4	2	0.15	0.65	0.08	0.4	0.99	0.99	Edit

PV Installation Details

ID	Peak Power	PV Efficiency	DC Losses	DC Joule Losses	Inverter Efficiency	AC Joule Losses	Actions
1	3	0.9	0.05	0.01	0.99	0.005	Edit
2	3.5	0.92	0.05	0.01	0.99	0.005	Edit
3	4	0.94	0.05	0.01	0.99	0.005	Edit
4	0	0.96	0.05	0.01	0.99	0.005	Edit

Figure 4.22: Installation Settings page



Your Communities

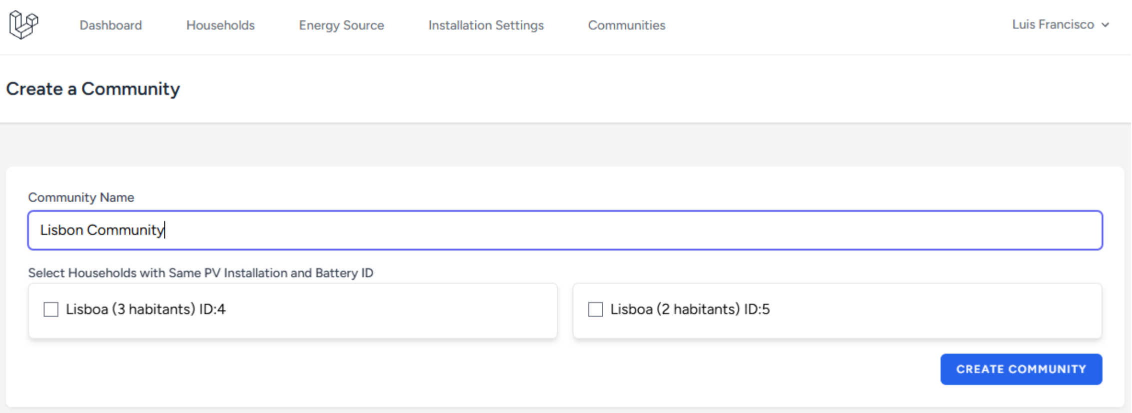
COMMUNITY NAME	BATTERY ID	HOUSEHOLDS	ACTIONS
Pombal	1	Pombal (4 habitants), Pombal (3 habitants), Pombal (6 habitants),	View Predictions Delete

Figure 4.23: Communities page

- **View Community Predictions** - Access predictions generated for the entire community.
- **Delete a Community** - Remove an existing community (admin-only feature).
- **Create a New Community** - Add a new community based on predefined rules(admin-only feature).

To create a new community, certain criteria must be met. For instance, all households within the community must be located in the same geographical area. While this page currently supports full testing capabilities, standard users will not have the ability to delete or add communities directly in a production environment.

The Community Creation page, illustrated in figure 4.24, displays all available households that meet the criteria for inclusion in a new community.



Create a Community

Community Name: Lisbon Community

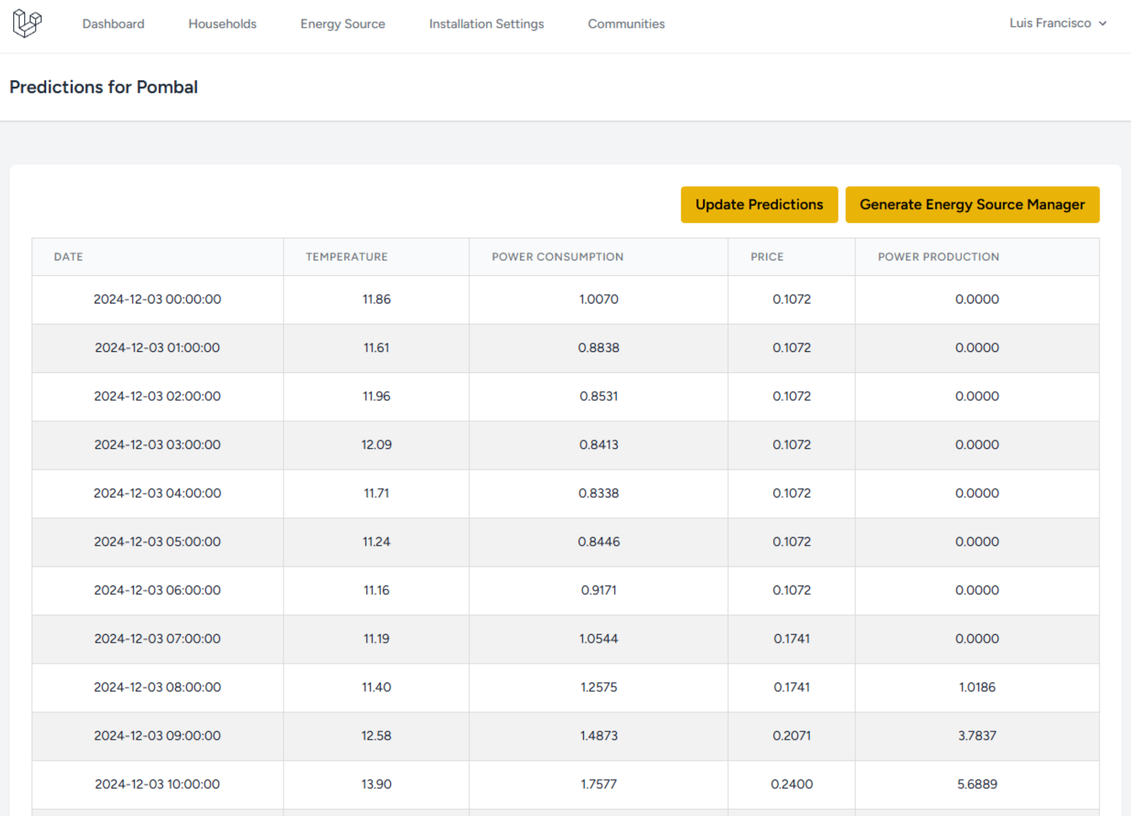
Select Households with Same PV Installation and Battery ID

☐ Lisboa (3 habitants) ID:4

☐ Lisboa (2 habitants) ID:5

Figure 4.24: Communities Creation page

The Community Predictions page, shown in figure 4.25, functions similarly to the Household Predictions page.



Predictions for Pombal

DATE	TEMPERATURE	POWER CONSUMPTION	PRICE	POWER PRODUCTION
2024-12-03 00:00:00	11.86	1.0070	0.1072	0.0000
2024-12-03 01:00:00	11.61	0.8838	0.1072	0.0000
2024-12-03 02:00:00	11.96	0.8531	0.1072	0.0000
2024-12-03 03:00:00	12.09	0.8413	0.1072	0.0000
2024-12-03 04:00:00	11.71	0.8338	0.1072	0.0000
2024-12-03 05:00:00	11.24	0.8446	0.1072	0.0000
2024-12-03 06:00:00	11.16	0.9171	0.1072	0.0000
2024-12-03 07:00:00	11.19	1.0544	0.1741	0.0000
2024-12-03 08:00:00	11.40	1.2575	0.1741	1.0186
2024-12-03 09:00:00	12.58	1.4873	0.2071	3.7837
2024-12-03 10:00:00	13.90	1.7577	0.2400	5.6889

Figure 4.25: Communities Predictions page

It allows users to update predictions or generate energy sources for the community. The energy management page for communities mirrors the one shown in figure 4.20 ensuring a consistent user experience across individual households and community-level management.

4.7 Simulations Parameters and Methodologies

To ensure a fair comparison across all experiments in Chapter 5, all simulations follow a consistent set of assumptions and equations. This section introduces the fixed parameters and cost-related formulas used throughout the analysis.

The following fixed parameters were used for the PV installation simulation:

- **PV efficiency** - The panel efficiency given by the manufacturer. Typically around 95%.
- **DC losses** - General losses that occur in the direct current circuit (dirt, shading, mismatch). Typically assumed at 2-3%.
- **DC Joule losses** - Energy lost as heat in DC wiring due to resistance. Usually estimated around 1%.
- **Inverter efficiency** - The efficiency of converting DC electricity into AC electricity, typically 96-99% for modern string inverters.
- **AC Joule losses** - Losses in the alternating current circuit (cables and distribution), generally assumed to be 1-2%.

These parameters were chosen based on typical high-efficiency solar panels available at the time this dissertation was written.

The following fixed parameters were used for the battery simulation:

- **SoH** - Indicates the current condition of the battery compared to its original capacity. A value of 80% reflects a used battery no longer suitable for electric vehicles.
- **Initial SoC** - The battery's charge level at the beginning of the simulation. Set to 25% in all experiments to ensure consistent initialization.
- **Charge rate** - Defines how fast a battery can be charged. A 0.5C rate, for example, means the battery charges in 2 hours.
- **Discharge rate** - Defines how fast a battery can be discharged. A 1C rate means the battery discharges in 1 hour.
- **Charge efficiency** - Represents the amount of energy successfully stored during charging.
- **Discharge efficiency** - Represents the energy that can be retrieved from the battery.

All simulations follow the following equations (4.8, 4.9, 4.10) to get an economical perspective of each case scenario.

These equations depend on the equipment's lifetime. For the inverter's lifetime, it may very depending on brand, model, environmental conditions, and maintenance. Inverter's manufactures often provide guarantee from 12 to 25 years.

The following lifetime assumptions were made based on manufacturers and research:

- **Inverter** - 16 years
- **Used battery** - 16 years (when used between 15-65% SoC limits)
- **PV installation** - 25 years
- **Installation services** - 16 years

The battery installation cost is the sum of the battery, inverter and installation cost. These costs are divided by the lifetime in weeks to convert into €/week which facilitate the "Total Cost" variable.

$$\text{Battery Installation Cost(€/week)} = \frac{\text{Battery Cost}}{\text{Battery Lifetime}} + \frac{\text{Inverter Cost}}{\text{Inverter Lifetime}} + \frac{\text{Installation Cost}}{\text{Installation Lifetime}} \tag{4.8}$$

The total cost follows the following equation:

$$\text{Total Cost(€/week)} = \text{Energy Cost} + \frac{\text{PV Cost}}{\text{PV Lifetime}} + \text{Battery Installation Cost} \tag{4.9}$$

Energy Cost is retrieved from the WattFuture website, referring to the energy cost throughout a week for each case scenario in both summer and winter season.

As for the reduction column, it follows an equation that relates each case scenario total cost with the grid only scenario and outputs a percentage that reflect how much better is that approach.

$$\text{Reduction(\%)} = \frac{\text{'Grid Only' Total Cost} - \text{'Case Scenario' Total Cost}}{\text{'Grid Only' Total Cost}} \times 100 \tag{4.10}$$

This reduction metric will reflect how much better is a certain case scenario over the base scenario that is the 'Grid Only'. The higher this number gets, the faster is the return of investment. Negative reduction values indicate scenarios where investment in additional storage or PV capacity does not provide cost savings compared to using grid energy alone.

The following equation shows an example of a 5kWh battery controlled by WF to extend its lifetime to 16 years. With that, a 3kWp PV installation was consider with a lifetime of 25 years.

$$\text{Battery Installation Cost(€/week)} = \frac{500}{16 \times 52} + \frac{600}{16 \times 52} + \frac{400}{16 \times 52} \tag{4.11}$$

$$\text{Total Cost(€/week)} = 8.11 + \frac{4000}{25 \times 52} + 1.80 = 12.97 \tag{4.12}$$

5

EVALUATION SCENARIOS AND RESULTS

This chapter details how WattFuture has been tested and how it performs. From getting accurate results from the predictive models to getting positive results when the energy source is controlled by the model.

5.1 Experimental Setup

After carefully selecting the right predictive model and ensuring that the new data is well stored, this information is now used in WattFuture's energy management system to optimize energy allocation.

In order to fairly evaluate the output of the WattFuture model, three case scenarios were tested each time the model was used to compare them and conclude whether there is a positive result when using WattFuture (WF). Section 3.3 explains each case scenario tested.

To gain a better understanding of the model's behavior, several tests were conducted for each case scenario. Each experiment was studied with different variables, including battery capacity, PV settings and battery limits to determine the ideal conditions to operate this software.

All experiments in the following subsections assume the following fixed parameters for the PV installation:

- PV efficiency: 95%
- DC losses: 5%
- DC Joule losses: 1%
- Inverter efficiency: 99%
- AC Joule losses: 0.5%

These parameters were chosen based on typical high-efficiency solar panels available at the time this dissertation was written. DC losses refers to general losses such as shading, degradation, Maximum Power Point Tracking (MPPT) inefficiencies and more. DC Joule losses and AC Joule losses refers to the energy loss as heat in the cables.

Additionally, the following fixed parameters were assumed for the battery:

- SoH: 80%
- Initial SoC: 25%
- Charge rate: 0.1C
- Discharge rate: 0.5C
- Charge efficiency: 0.99%
- Discharge efficiency: 0.99%

A state of health of 80% represents an used battery that is no longer suitable for EV's. For the simulation to function correctly, an initial charge percentage had to be assigned. All simulations assumed 25% as the initial battery state.

The battery charging and discharging rate is measured as C-rate, meaning that a fully charged battery with a capacity of 10Ah and 1C discharge rate should be able to provide 10 Amperes for one hour. Efficiency values were assumed based on average values reported in battery manufacturer datasheets.

The following table 5.1 present all PV installation prices that were considered in the simulations. All installations assume a lifetime of 25 years based on the average PV lifetime of the panels available at the moment.

Table 5.1: PV Installation Costs

Peak Power (kW)	**Installation Cost (€)**	**Installation Weekly Cost (€/week)**
1	2000	1,54
2	3200	2,46
3	4000	3,08
4	4800	3,69

These prices were obtained through a simulation in GALP's website GALP (2025). As peak power increases, the €/kWp decreases since the majority of the cost is incurred in the installation process rather than the panels themselves.

GALP's website also provides information about a new 5kWh battery (LUNA2000-5-S0), with a cost of 3500€ associated with it, which equates to 700€/kWh. This price includes the inverter and installation costs.

SLB market prices remains unstable and difficult to establish. However, at the time this dissertation was written, a website called "Second Life EV Batteries" Ltd (2025), was selling them for approximately €100/kWh. For simulations proposes, the following table 5.2 represent the battery installation cost that were assumed during the experiments.

To be clear, these prices were retrieved from sources available at the time of writing (2025) and may suffer significant fluctuations in the future.

Many commercial battery kits, such as those offered by GALP, bundle the battery, inverter and installation into a single price, making it difficult to determine the individual cost components. For example, the GALP kit with a 5 kWh LUNA2000-5-S0 battery is priced at around 3,500€, including inverter and installation. In comparison, the same battery is sold on platforms such as SUNSHOP (2025) for around 3,000€, excluding these services.

In order to estimate a fair and transparent cost breakdown for second-life batteries, the values used in the table 5.2 assume an inverter and installation cost of 1,000€ (600€ for the inverter and 400€ for the installation cost) for a 5 kWh system, slightly higher than the estimated 500€ difference observed in commercial offers. This conservative approach helps to maintain realism, while giving second-life batteries a fair basis for comparison.

Table 5.2: Second-Life Batteries Installation Cost

Capacity (kWh)	**Battery's Cost (€)**	**Inverter's Cost (€)**	**Installation Cost (€)**	**Total Cost (€)**
2,5	250	300	350	1000
5	500	600	400	1500
10	1000	1000	500	2500

For the inverter's lifetime, it may very depending on brand, model, environmental conditions, and maintenance. Inverter's manufactures often provide guarantee from 12 to 25 years. As so, an average lifetime of 16 years was consider, the same as an used battery being controlled from 15% to 65%.

The following scenarios will be simulated in the upcoming subsections:

- **Battery Capacity** - Simulate different battery capacities to understand the WF model behavior in each situation.
- **Battery Limits** - Verify whether if it is really worth limiting the battery to extend its lifetime even if it is not efficient in the short term.
- **PV Installation** - Important to understand how the PV installation peak power affects the WF model.
- **New Battery vs SLB** - Simulate the difference between using WF model with a new battery and an old one.

5.2 Battery Capacity Impact

The first set of simulations aim to identify the model's behavior when operating different battery sizes. In these first set of experiments, a 1kWp PV Installation was consider and and the battery was limited to a range of 15%-65% in both "WattFuture" and "PV + Battery" scenario to allow a fair capacity comparison between scenarios.

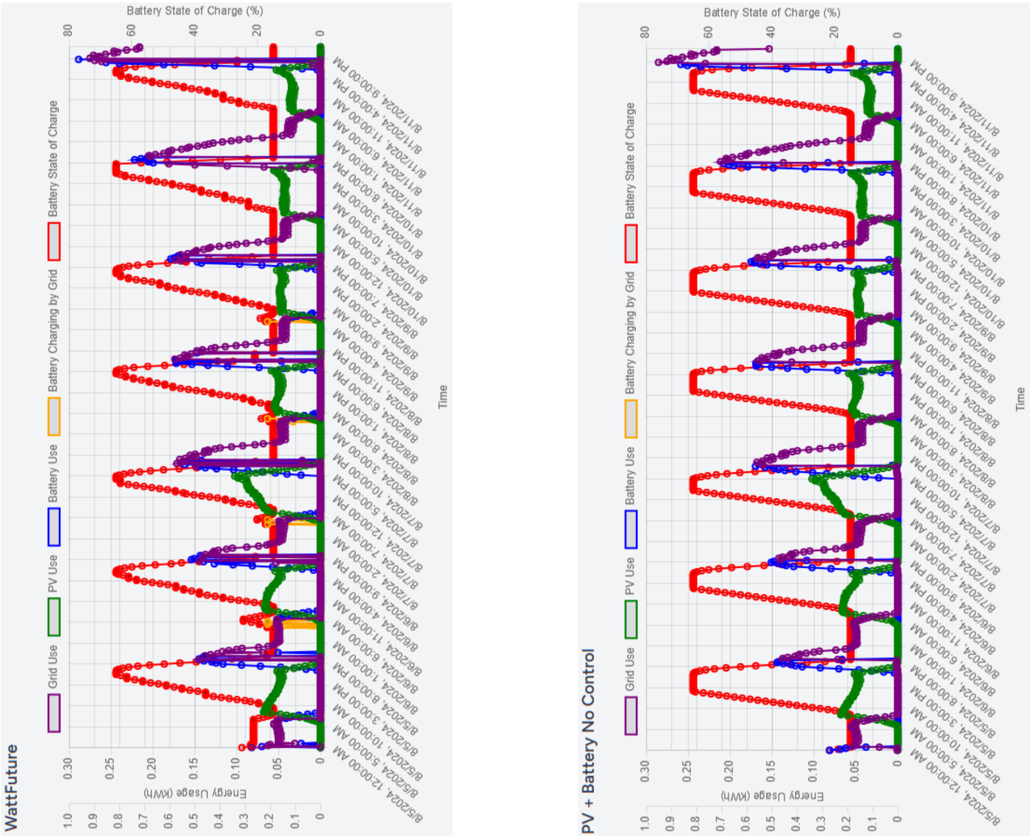
First experiment considers a 1kWp PV Installation costing 2000€ and a 2,5kWh battery, costing 1000€, limited to a 15-65% usage range, which means an expected lifetime of 16 years. In this conditions, the PV installation weekly cost will be 1,54€ and the battery weekly cost will be 1,20€.

Table 5.3: 2,5kWh Battery Results (Summer and Winter)

Case Scenario	**Energy Cost (€/week)**		**Total Cost (€/week)**		**Reduction (%)**	
	Summer	**Winter**	**Summer**	**Winter**	**Summer**	**Winter**
Grid Only	7,77	14,7	7,77	14,7	0,00%	0,00%
With PV	4,17	12,4	5,71	13,94	26,53%	5,18%
PV + Battery	2,96	11,91	5,70	14,65	26,64%	0,34%
WattFuture	2,87	11,08	5,61	13,82	27,79%	5,98%

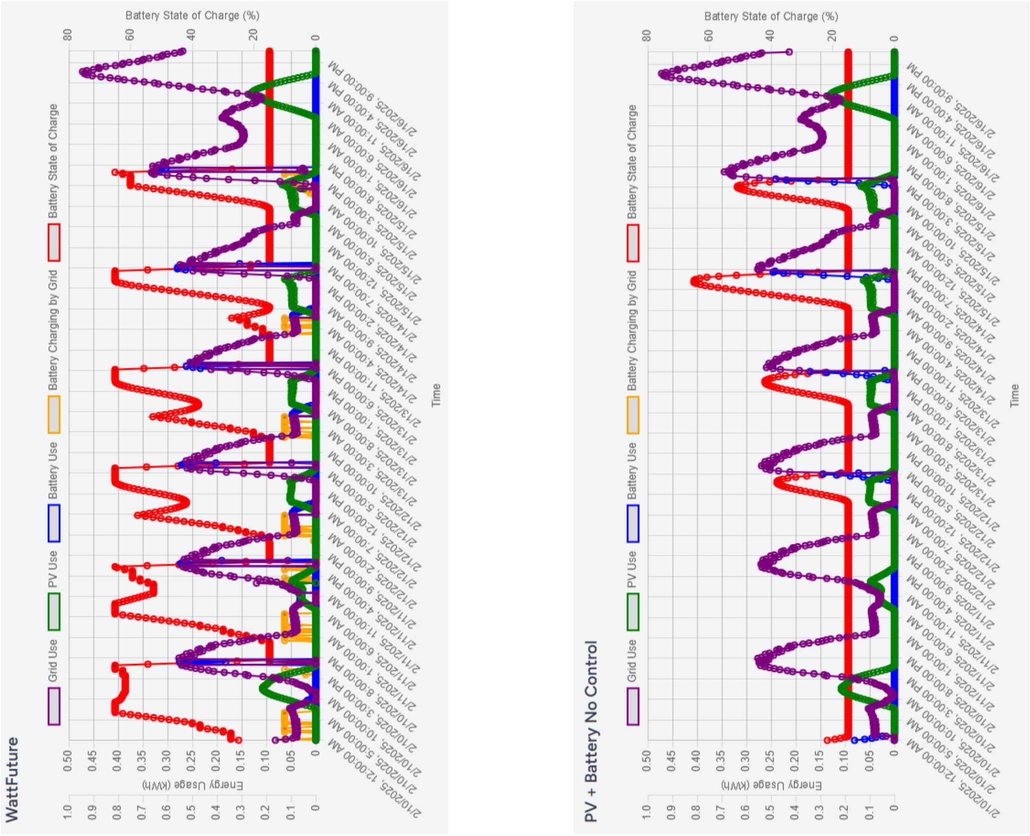
Table 5.3 and figures 5.1 reveals that a small battery might struggle during winter if there is not a proper management, since the third case scenario, PV plus Battery is barely positive over the base scenario. However, with WattFuture, that struggle seems to have less impact, managing to have the higher reduction percentage of all case scenarios.

Looking at the summer season, it is also noticeable that, with a smaller battery, WattFuture doesn't perform that much better than the case scenario without WF. This is due to the fact that the battery is now able to fully charge from PV production and doesn't have to rely on the grid as much, visible in the following graphs 5.1. Combining this with the fact that the battery doesn't have enough energy to cover energy consumption and we end up having two very similar behaviors in both case scenarios with a battery.



(a) WattFuture (Summer)

(b) PV + Battery (Summer)



(c) WattFuture (Winter)

(d) PV + Battery (Winter)

Figure 5.1: 2,5kWh Battery Graphical Results (Summer and Winter)

The second experiment considers a 1kWp PV Installation costing 2000€ and a 5kWh battery, costing 1500€, limited to a 15-65% usage range, which means an expected lifetime of 16 years. In this conditions, the PV installation weekly cost will be 1,54€ and the battery weekly cost will be 1,80€.

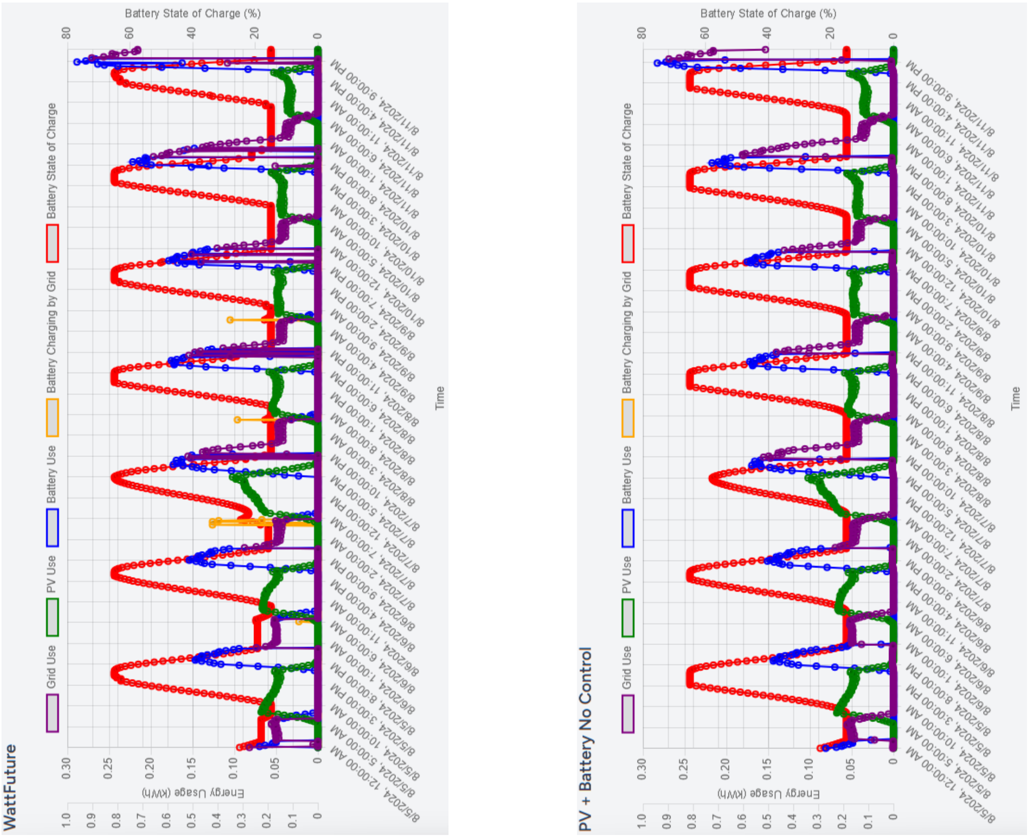
Following the same principle as before, both scenarios with batteries use a limited range battery to provide consistency between experiments, targeting only the battery capacity.

Table 5.4: 5kWh Battery Results (Summer and Winter)

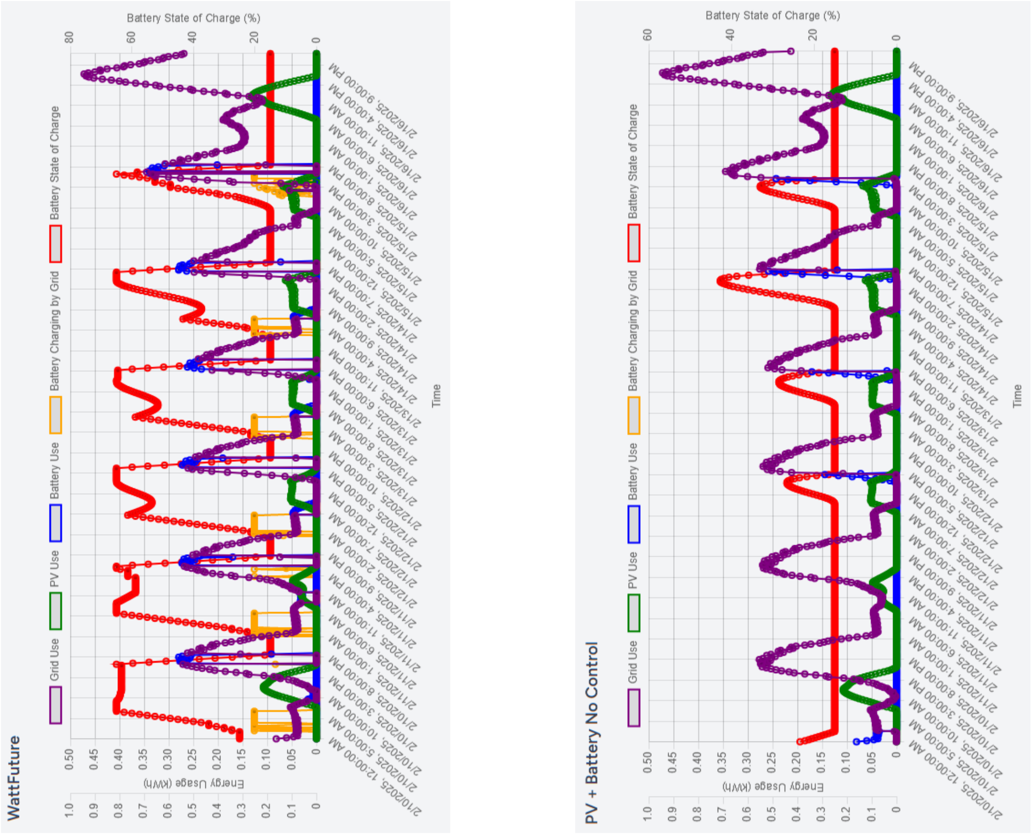
Case Scenario	**Energy Cost (€/week)**		**Total Cost (€/week)**		**Reduction (%)**	
	Summer	**Winter**	**Summer**	**Winter**	**Summer**	**Winter**
Grid Only	7,77	14,7	7,77	14,7	0,00%	0,00%
With PV	4,17	12,4	5,71	13,94	26,53%	5,18%
PV + Battery	1,80	11,85	5,14	15,19	33,83%	-3,34%
WattFuture	1,74	10,16	5,08	13,50	34,60%	8,15%

In this experiment, the first negative reduction percentage appears, as the initial high cost of the battery will impact the total cost to a value higher than the 'Grid Only' scenario.

Table 5.4 and figures 5.2 reflects even further the difference when controlling the battery with and without WF. Even thought the reduction percentage is higher than the first experiment for the battery case scenarios during summer, the scenario with no control had a significant reduction drop during winter while the scenario with WF manages to improve its performance during both seasons. This experiment proves that using a battery with no control can be as good as WattFuture in some specific situations but might underperform when dealing with limited resources, resulting in a major annual difference between both scenarios.



(a) WattFuture (Summer) (b) PV + Battery (Summer)



(c) WattFuture (Winter) (d) PV + Battery (Winter)

Figure 5.2: 5kWh Battery Graphical Results (Summer and Winter)

Last experiment uses a 1kWp PV Installation costing 2000€ and a 10kWh battery, costing 2500€, limited to a 15-65% usage range, which means an expected lifetime of 16 years. In this conditions, the PV installation weekly cost will be 1,54€ and the battery weekly cost will be 3,00€.

Table 5.5: 10kWh Battery Results (Summer and Winter)

Case Scenario	**Energy Cost (€/week)**		**Total Cost (€/week)**		**Reduction (%)**	
	Summer	**Winter**	**Summer**	**Winter**	**Summer**	**Winter**
Grid Only	7,77	14,7	7,77	14,7	0,00%	0,00%
With PV	4,17	12,4	5,71	13,94	26,53%	5,18%
PV + Battery	1,33	11,8	5,87	16,34	24,41%	-11,18%
WattFuture	1,20	9,15	5,74	13,69	26,08%	6,85%

Table. 5.5 reveals that increasing the capacity turns out to be not ideal for this household as reduction percentages drop significantly.

As expected, while a high capacity battery can lead to higher savings in summer, its value diminishes in winter due to limited PV generation. The high upfront cost makes it a less effective investment year-round. It reaches a point where the user would lose money during winter by using a battery that is not capable of charging from the grid or providing energy during critical hours.

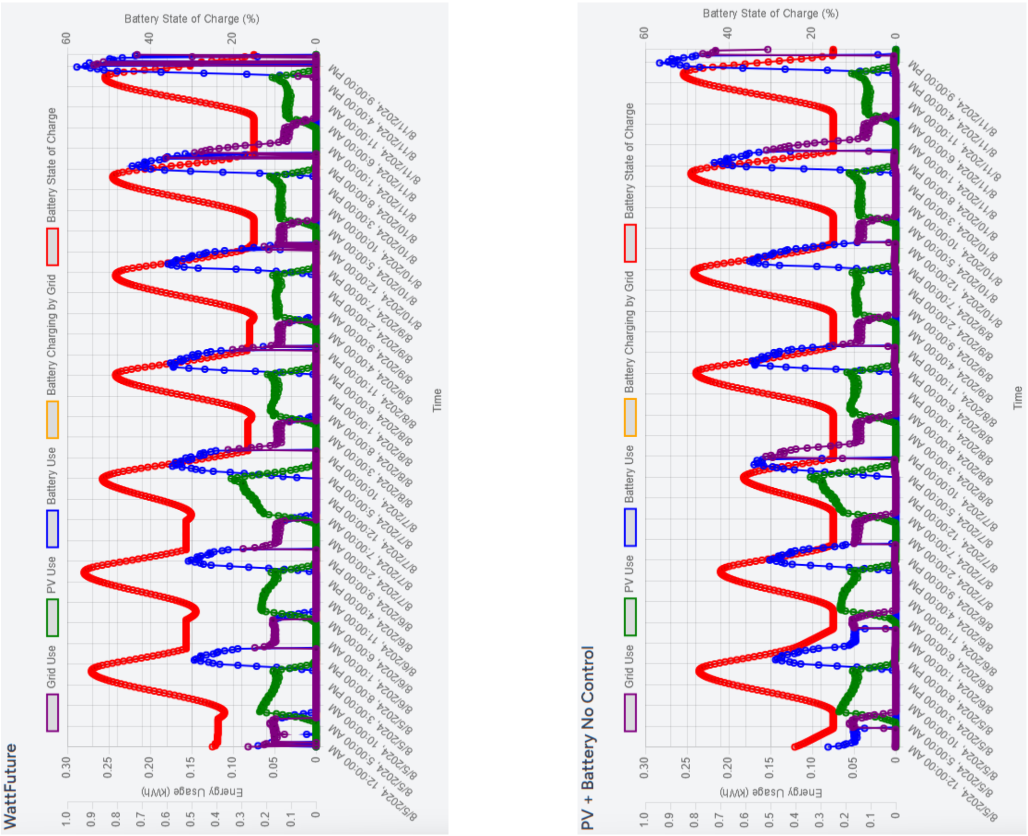
Additionally, this experiment shows that even WattFuture is underperforming during summer compared to the scenario "PV Only", even with a 3 times less energy cost. This is due to the battery's high cost that immediately increase the total cost higher than the 'With PV' scenario. Notice that during winter, WF manages to outperform 'With PV' scenario even with high and unnecessary investments.

The following graphs 5.3 show that WF ability to charge from the grid during winter makes a significant positive impact in the reduction percentage.

Table 5.6: Battery Capacity Summary Results (Summer and Winter)

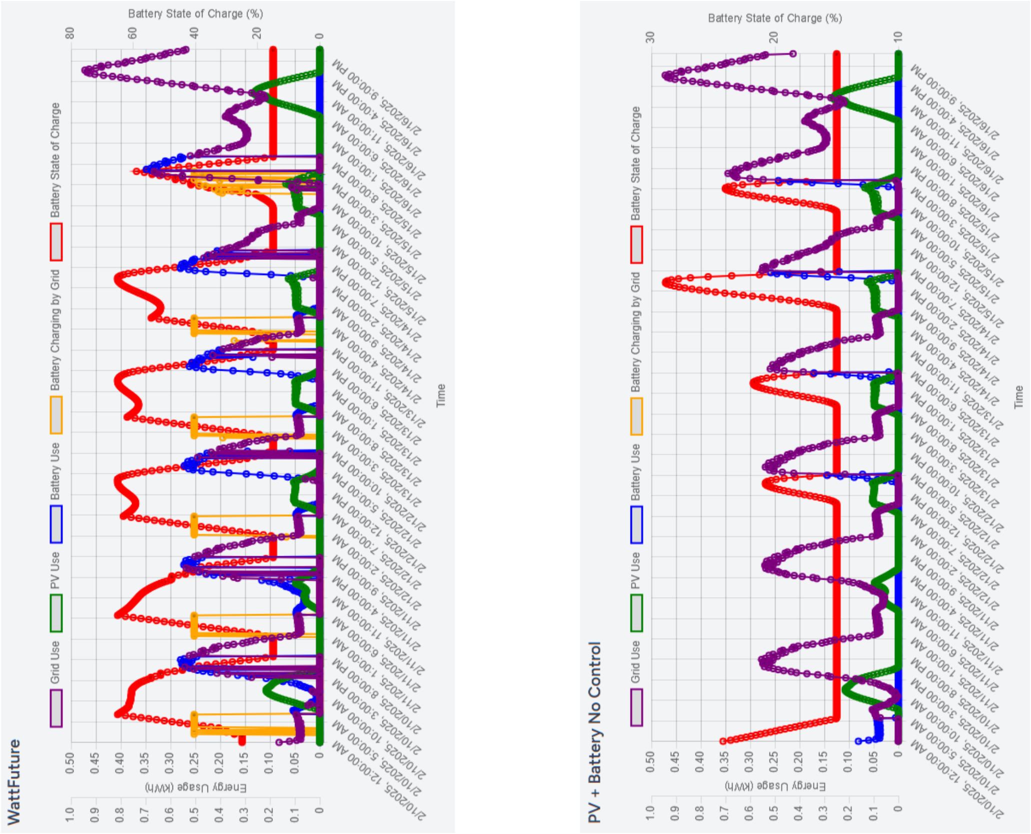
Battery Size **(Table ref.)**	**WF Reduction (%)**		**No Control Reduction (%)**		**PV Only Reduction (%)**	
	Summer	**Winter**	**Summer**	**Winter**	**Summer**	**Winter**
2.5 kWh (5.3)	27.79%	5.98%	26.64%	0.34%	26.53%	5.18%
5 kWh (5.4)	34.60%	8.15%	33.83%	-3.34%	26.53%	5.18%
10 kWh (5.5)	26.08%	6.85%	24.41%	-11.18%	26.53%	5.18%

Table 5.6 summarizes the results of all experiments in this scenario. It highlights that while increasing battery capacity may improve summer performance, it often leads to diminishing returns in winter, especially without intelligent control. The WattFuture strategy consistently outperforms the scenario with no control, particularly in winter, proving its ability to better manage limited energy resources.



(a) WattFuture (Summer)

(b) PV + Battery (Summer)



(c) WattFuture (Winter)

(d) PV + Battery (Winter)

Figure 5.3: 10kWh Battery Graphical Results (Summer and Winter)

5.3 Battery Limits Impact

Previous simulations were necessary to identify the impact that the battery's capacity has in this type of investment. Another factor we should consider is the batteries limitations, whether it's better to save the battery for longer lifetime and lower costs reduction or extend those limits that will shorten the lifetime bue will improve instant profit.

The following simulations are going to test this theory by using a 5kWh battery with different limits, firstly 15-95% range for both battery scenarios and a second experiment with a new battery for the battery scenario with no control. This 15-95% range was selected to be compatible with figure 2.4. This way it's possible to assume an expected lifetime of the battery.

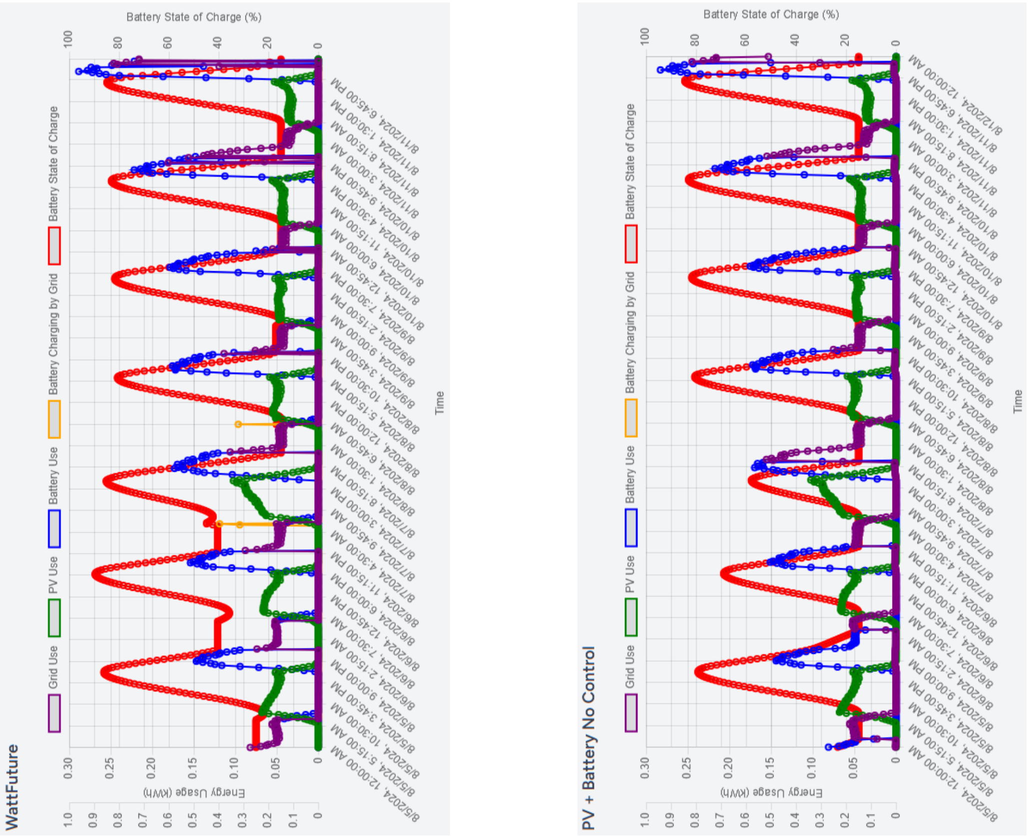
The first experiment forces the battery lifetime to drop to 8 years, which increases the cost per week. In this conditions, the 1kWp PV installation weekly cost will be 1,54€ and the 5kWh battery weekly cost will be 3,37€.

Table 5.7: 5kWh with 15-95% Range Battery Results (Summer and Winter)

Case Scenario	**Energy Cost (€/week)**		**Total Cost (€/week)**		**Reduction (%)**	
	Summer	**Winter**	**Summer**	**Winter**	**Summer**	**Winter**
Grid Only	7,77	14,7	7,77	14,7	0,00%	0,00%
With PV	4,17	12,4	5,71	13,94	26,53%	5,18%
PV + Battery	1,39	11,85	6,29	16,75	19,00%	-13,97%
WattFuture	1,26	9,62	6,16	14,52	20,67%	1,20%

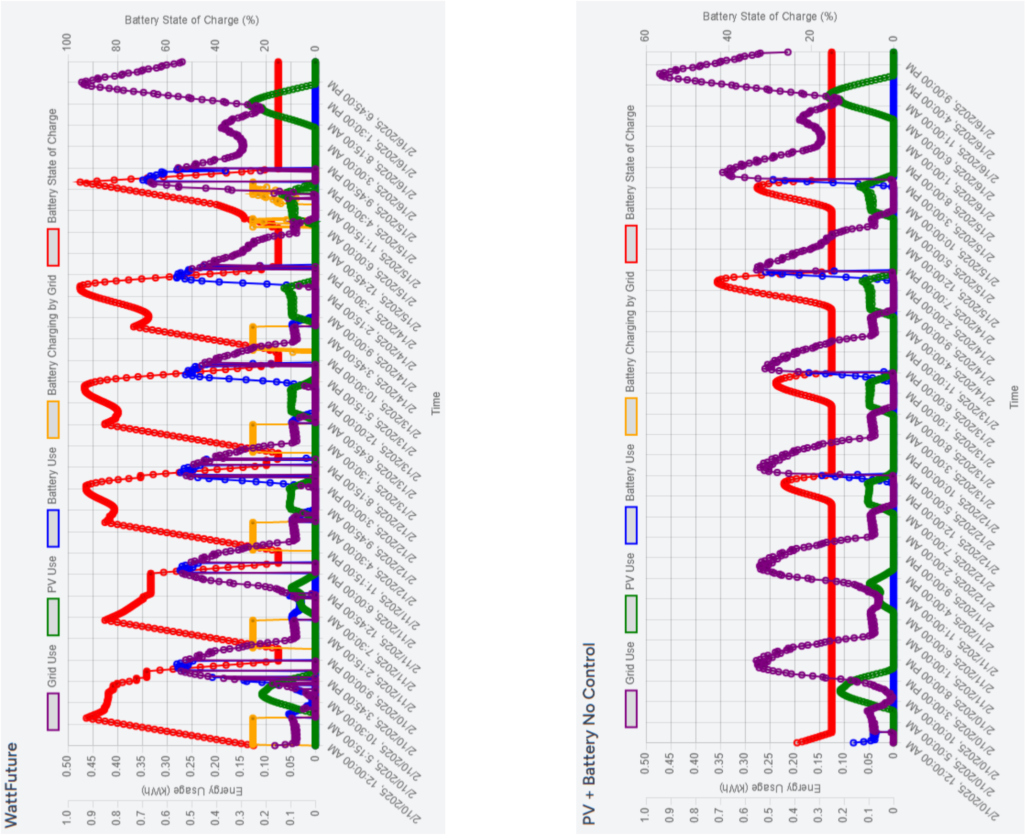
Limiting the battery to a 15-95% range results in major energy cost drops compared to the similar experiment 5.4 that uses a 15-65% range. However, as the battery limits increases, its lifetime decreases and, consequentially, the total cost will increase. This can be seen in the reduction column, where the percentage have dropped significantly.

The following graphs 5.4 also provide an important factor that might be affecting the reduction column. Notice that the battery barely reaches 95%, especially during winter, directly affecting the reduction percentage.



(a) WattFuture (Summer)

(b) PV + Battery (Summer)



(c) WattFuture (Winter)

(d) PV + Battery (Winter)

Figure 5.4: 5kWh with 15-95% Range Battery Graphical Results (Summer and Winter)

In the following experiment 5.8, a new 5kWh battery without WF is being compared to an used 5kWh battery that is being controlled by WF, with a limit range of 15-65%. In this conditions, the 1kWp PV installation weekly cost will be 1,54€, the used battery's weekly cost will be 1,80€ and the new battery's weekly cost will be 3,74€.

Table 5.8: 5kWh New Battery Results (Summer and Winter)

Case Scenario	**Energy Cost (€/week)**		**Total Cost (€/week)**		**Reduction (%)**	
	Summer	**Winter**	**Summer**	**Winter**	**Summer**	**Winter**
Grid Only	7,77	14,7	7,77	14,7	0,00%	0,00%
With PV	4,17	12,4	5,71	13,94	26,53%	5,18%
PV + Battery	1,31	11,77	6,59	17,05	15,22%	-15,97%
WattFuture	1,74	10,16	5,08	13,50	34,60%	8,15%

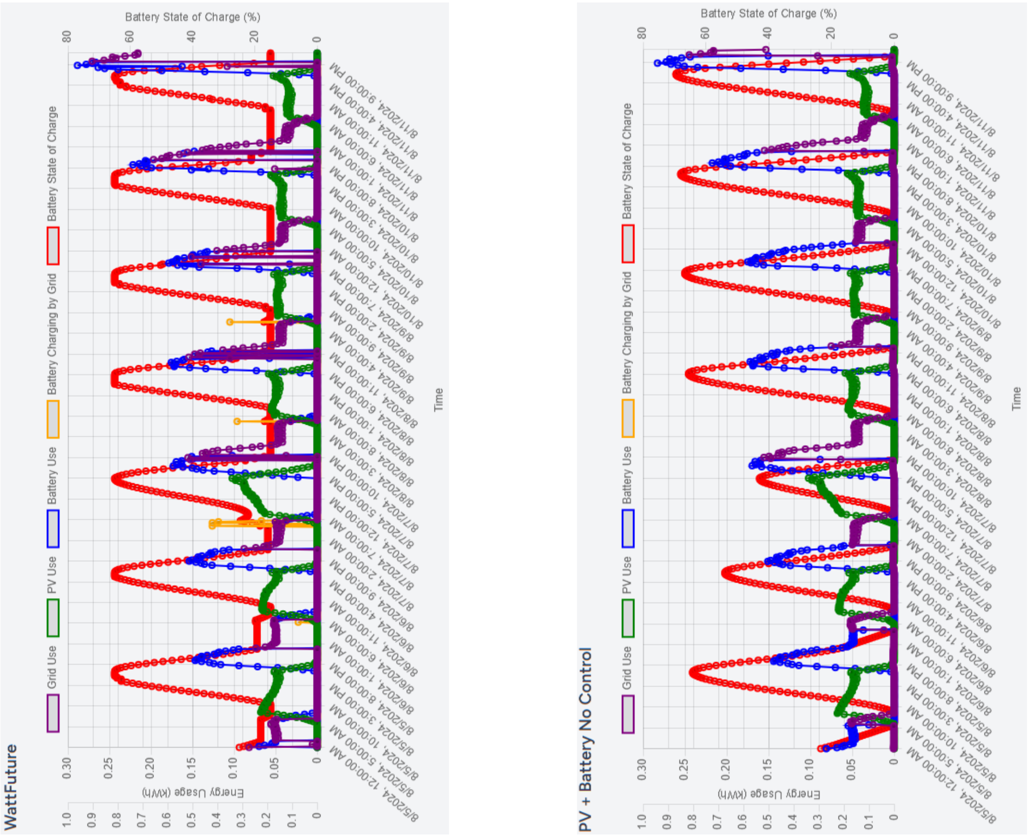
Previous table 5.8 reveals that a new unlimited battery can lower the energy bill during summer but this come with a greater investment that immediately drops the reduction percentage for both seasons. It is also noticeable that, during winter, the battery with no control is not able to charge properly, making it underperform compared to the WattFuture scenario.

The following graphs 5.5 give a better view for the case scenario without WF problem.

Table 5.9: Battery Limits Summary Results (Summer and Winter)

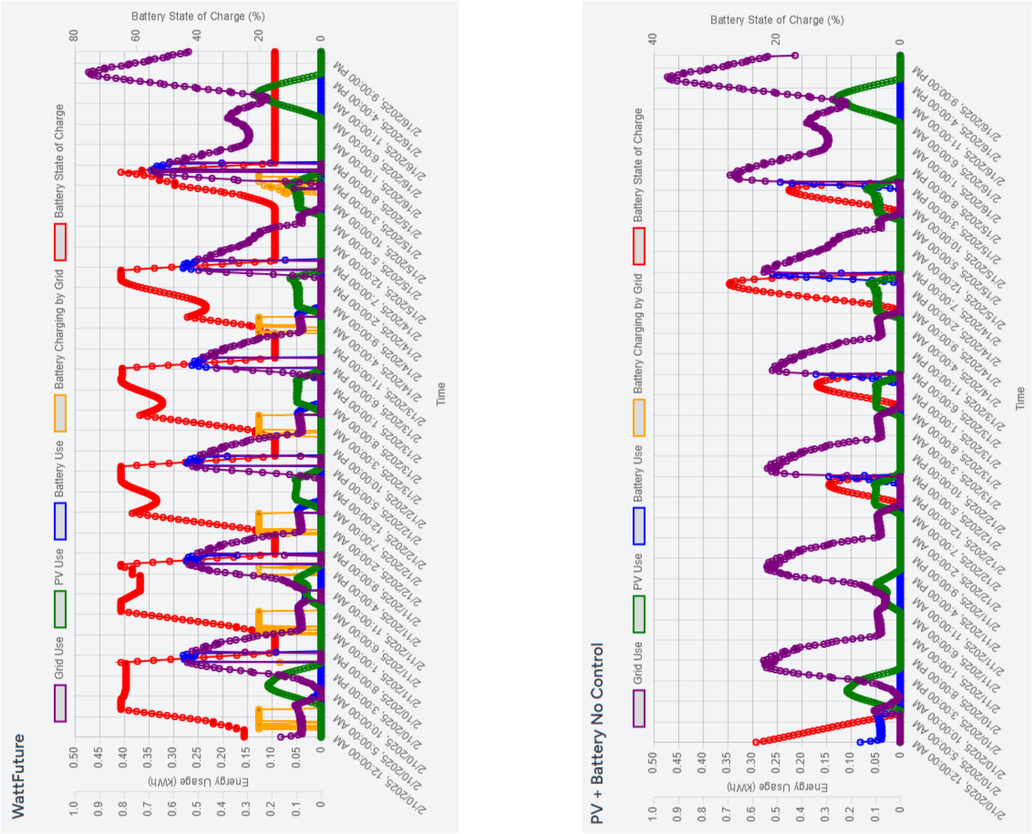
Battery Type (Table ref.)	**WF Reduction (%)**		**No Control Reduction (%)**		**PV Only Reduction (%)**	
	Summer	**Winter**	**Summer**	**Winter**	**Summer**	**Winter**
Used (15-95%) (5.7)	20.67%	1.20%	19.00%	-13.97%	26.53%	5.18%
New (No Limit) (5.8)	34.60%	8.15%	15.22%	-15.97%	26.53%	5.18%

Table 5.9 summarizes the impact of different battery usage ranges on reduction percentage. Although extending the battery limits or using a new battery can significantly reduce energy costs in summer, the overall investment cost often causes lower or even negative reduction values in winter due to the high initial investment (experiment 5.8) and lower lifetime (experiment 5.7). WattFuture consistently performs better across both seasons, especially when the battery is underused or facing unfavorable winter conditions.



(a) WattFuture (Summer)

(b) PV + Battery (Summer)



(c) WattFuture (Winter)

(d) PV + Battery (Winter)

Figure 5.5: 5kWh New Battery Graphical Results (Summer and Winter)

5.4 PV Installation Peak Power Impact

Following the same idea as the previous simulations, studying the impact that the PV installation peak power might have in the model should give an idea of its behavior.

All experiments in this subsection assume a 5kWh battery limited between 15% and 65% for both battery case scenarios, with and without WF.

The first experiment uses a 2kWp PV installation that cost 3200€ with a 5kWh used battery that costs 1500€. In this conditions, the PV installation weekly cost will be 2,46€ and the battery weekly cost will be 1,80€.

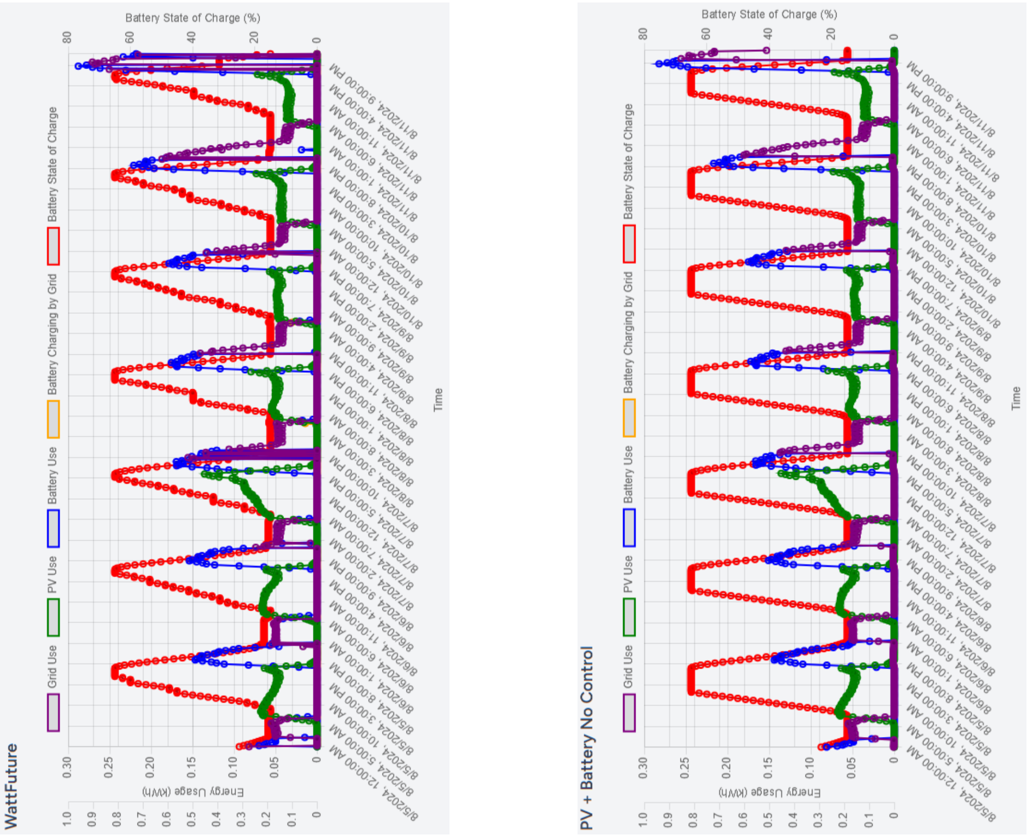
Table 5.10: 2kWp PV Installation Results (Summer and Winter)

Case Scenario	**Energy Cost (€/week)**		**Total Cost (€/week)**		**Reduction (%)**	
	Summer	**Winter**	**Summer**	**Winter**	**Summer**	**Winter**
Grid Only	7,77	14,70	7,77	14,70	0,00%	0,00%
With PV	2,93	11,22	5,39	13,68	30,59%	6,93%
PV + Battery	0,53	9,34	4,79	13,60	38,30%	7,45%
WattFuture	0,52	8,34	4,78	12,60	38,42%	14,26%

Comparing the results in the table 5.10 with the experiment 5.4, it's possible to verify that every scenario's result has improved which means that this household might benefit from higher peak power installations.

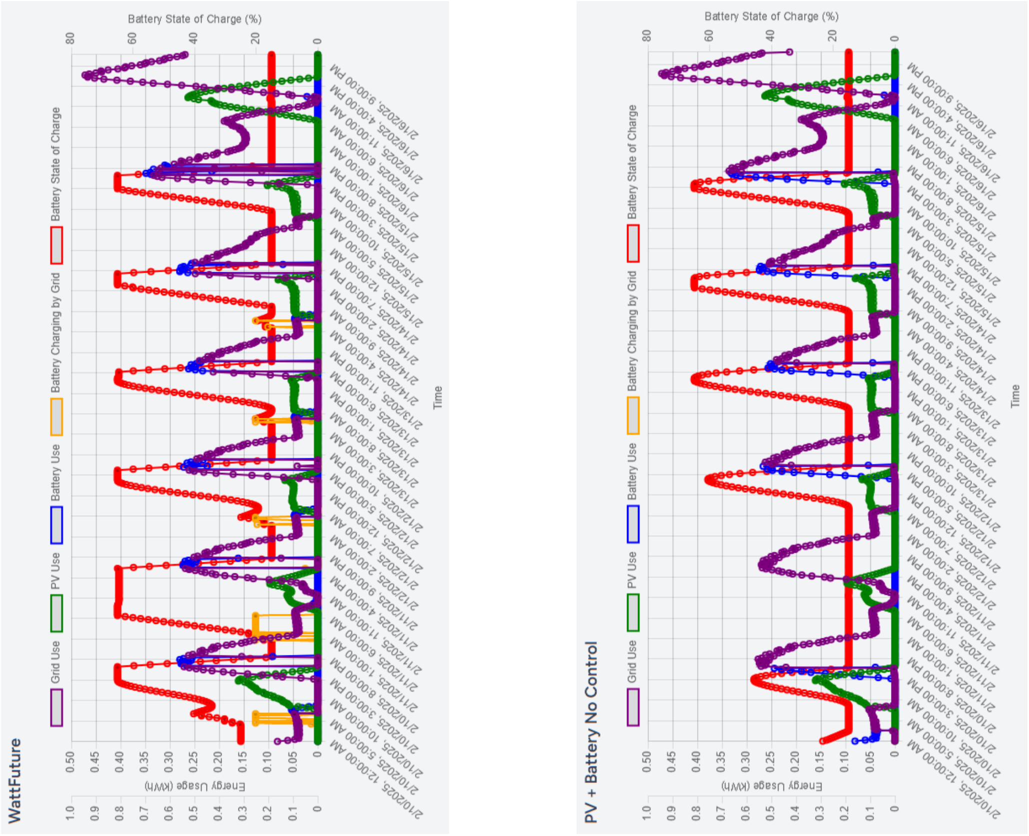
The following graphs 5.6 also reveals a significant improvement over the scenario with the battery without WF due to extra production that it's being stored in the battery.

WattFuture's model also improved its performance, maintaining a positive outcome. Not as much during summer but significantly higher during winter when compared to the scenario without WF.



(a) WattFuture (Summer)

(b) PV + Battery (Summer)



(c) WattFuture (Winter)

(d) PV + Battery (Winter)

Figure 5.6: 2kWp Photovoltaic Installation Graphical Results (Summer and Winter)

Second experiment uses a 3kWp PV installation that cost 4000€ with a 5kWh used battery that costs 1500€. In this conditions, the PV installation weekly cost will be 3,08€ and the battery weekly cost will be 1,80€.

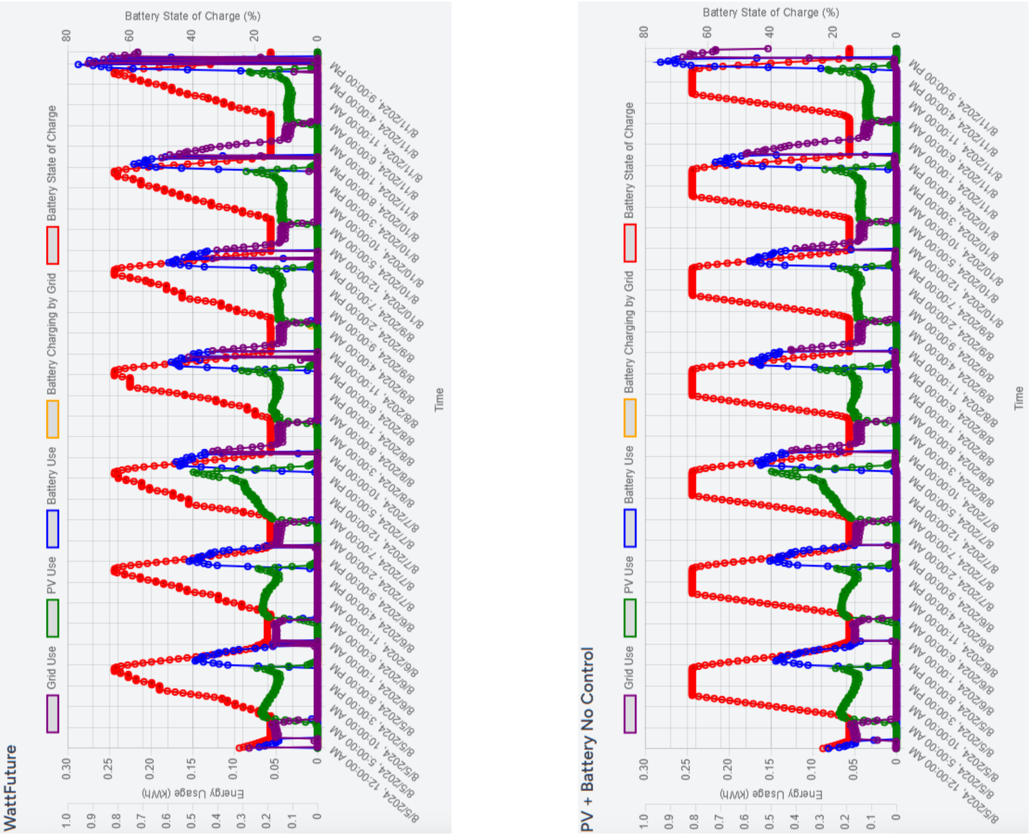
Table 5.11: 3kWp PV Installation Results (Summer and Winter)

Case Scenario	**Energy Cost (€/week)**		**Total Cost (€/week)**		**Reduction (%)**	
	Summer	**Winter**	**Summer**	**Winter**	**Summer**	**Winter**
Grid Only	7,77	14,70	7,77	14,70	0,00%	0,00%
With PV	1,82	10,40	4,89	13,48	36,98%	8,32%
PV + Battery	-0,57	8,09	4,31	12,97	44,53%	11,77%
WattFuture	-0,58	7,30	4,30	12,18	44,66%	17,14%

As results keep getting better, table 5.11 start to show negative values in the energy cost column during summer. This negative value represent a scenario where too much energy was being produced and had to be sold to the grid due to battery limitations. A value of 0,025€/kWh for energy sold was consider in all simulations. Even with extra energy being sold, this experiment seems to be profitable, as reduction percentages had increased.

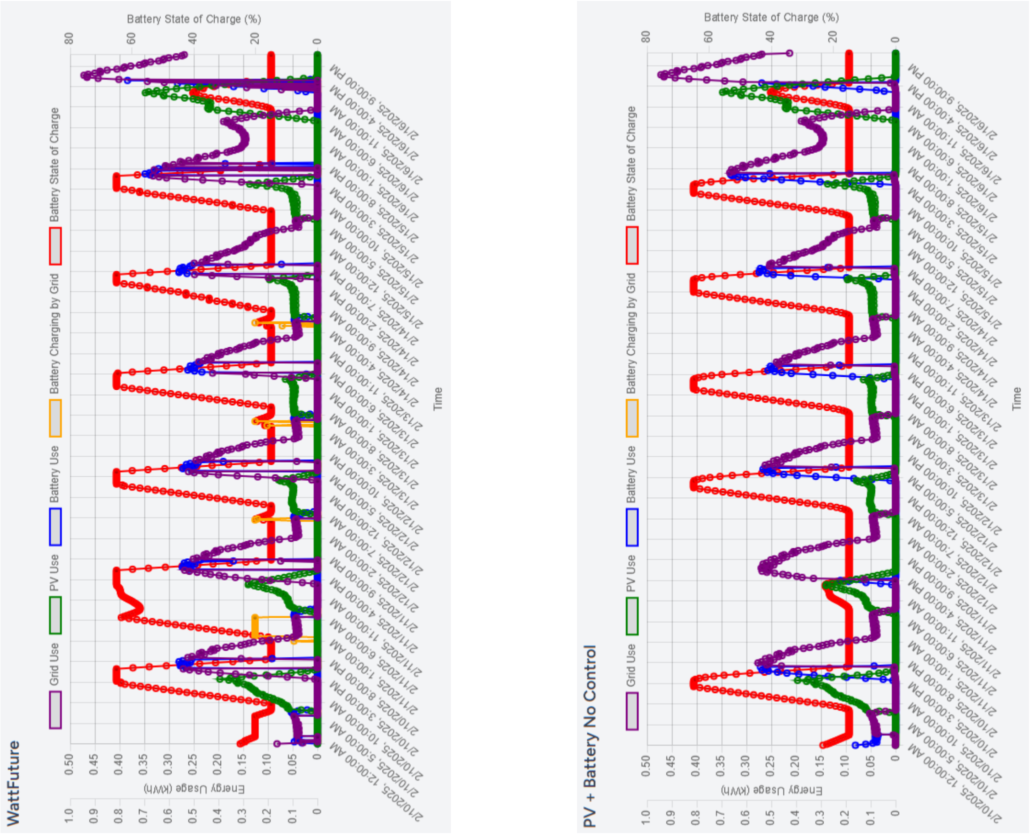
In these conditions, even the scenario without WF slowly reaches the scenario with WF's results. However, during winter, WF manages to be superior with some margin from the other scenarios.

Following graphs 5.7 help visualizing WF performance.



(a) WattFuture (Summer)

(b) PV + Battery (Summer)



(c) WattFuture (Winter)

(d) PV + Battery (Winter)

Figure 5.7: 3kWp Photovoltaic Installation Graphical Results (Summer and Winter)

Lastly, an experiment with a 4kWp PV installation that cost 4000€ was used. In this conditions, the PV installation weekly cost will be 3,69€ and the battery weekly cost will be 1,80€.

Table 5.12: 4kWp PV Installation Results (Summer and Winter)

Case Scenario	**Energy Cost (€/week)**		**Total Cost (€/week)**		**Reduction (%)**	
	Summer	**Winter**	**Summer**	**Winter**	**Summer**	**Winter**
Grid Only	7,77	14,70	7,77	14,70	0,00%	0,00%
With PV	0,75	9,76	4,44	13,45	42,83%	8,49%
PV + Battery	-1,63	7,20	3,87	12,70	50,25%	13,64%
WattFuture	-1,63	6,52	3,87	12,02	50,25%	18,26%

Table 5.12 shows that all results are better with every reduction percentage getting higher.

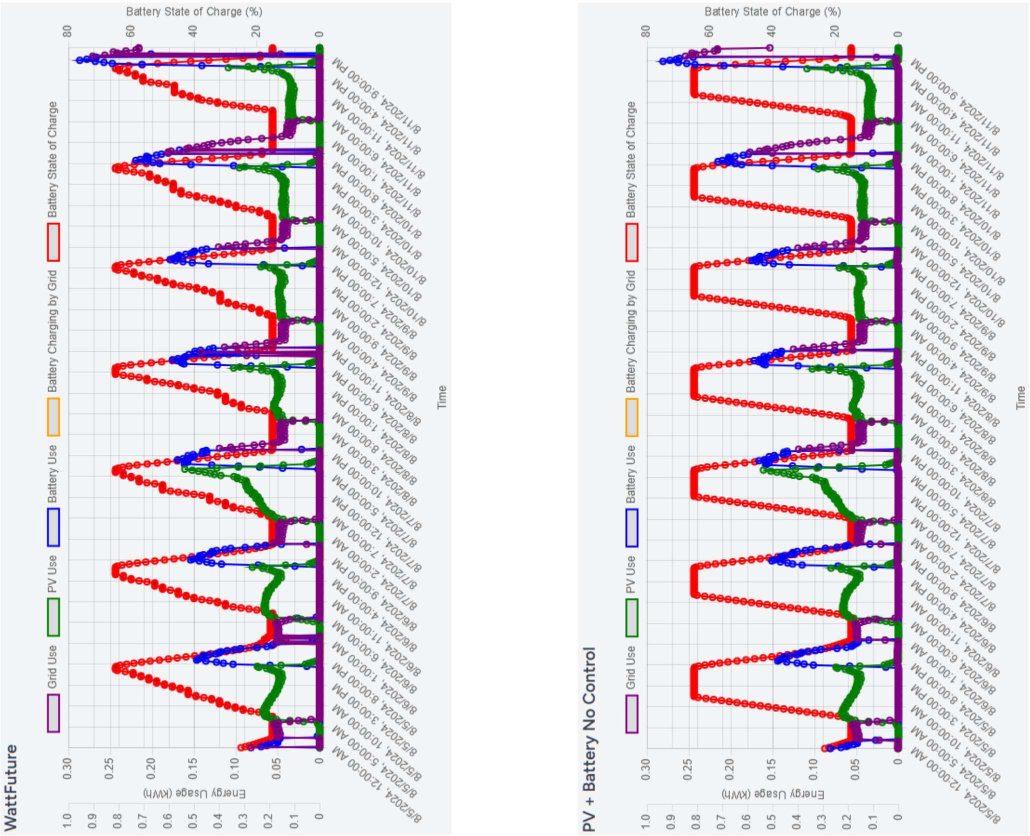
However, this simulation reveals that too much PV production might not be that beneficial as it reaches the battery limits sooner. Table 5.12 shows a slight increase in winter reduction percentage but a significant decrease during summer season which it's not ideal in long term.

From the graphs 5.8, it's possible to predict that more PV production won't be beneficial as too much energy is being sold to the grid at a low price.

Table 5.13: PV Peak Power Summary Results (Summer and Winter)

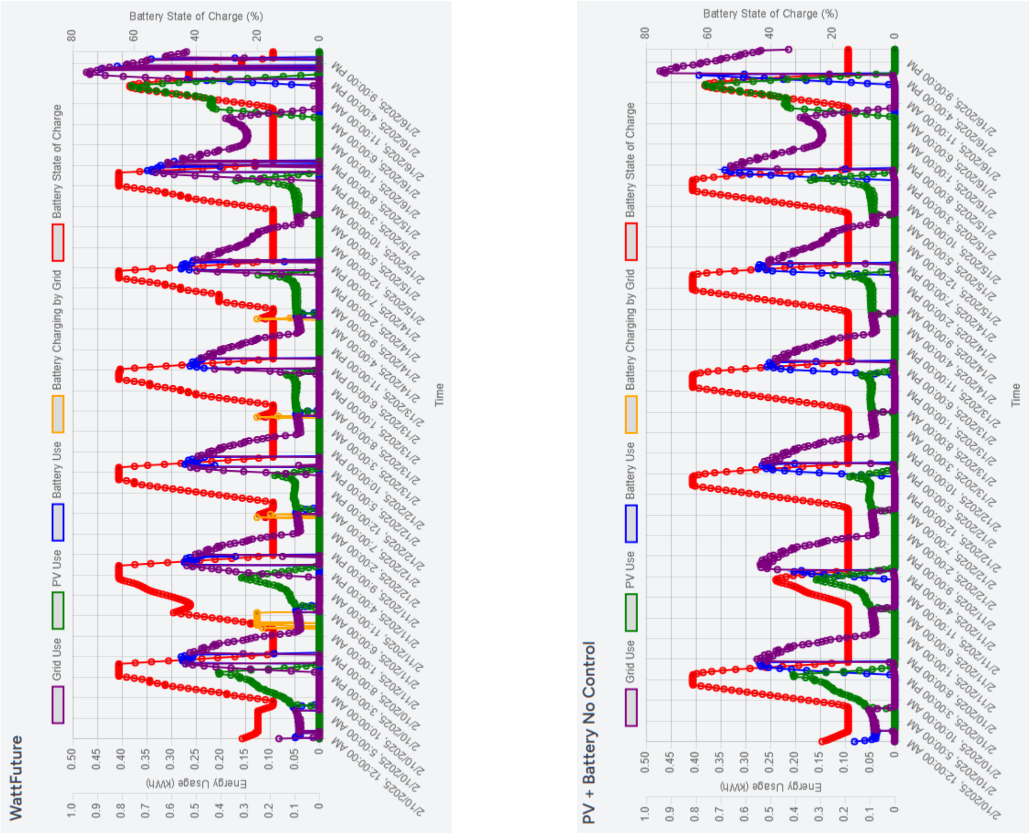
PV Size (Table ref.)	**WF Reduction (%)**		**No Control Reduction (%)**		**PV Only Reduction (%)**	
	Summer	**Winter**	**Summer**	**Winter**	**Summer**	**Winter**
2 kWp (5.10)	38.42%	14.26%	38.30%	7.45%	30.59%	6.93%
3 kWp (5.11)	44.66%	17.14%	44.53%	11.77%	36.98%	8.32%
4 kWp (5.12)	50.25%	18.26%	50.25%	13.64%	42.83%	8.49%

Table 5.13 compares the reduction percentages across varying PV installation sizes. As expected, higher PV peak power tends to improve overall performance, particularly in summer. However, the 4 kWp scenario also shows signs of diminishing returns, as excess energy is sold to the grid at low prices, limiting cost reduction during peak generation periods.



(a) WattFuture (Summer)

(b) PV + Battery (Summer)



(c) WattFuture (Winter)

(d) PV + Battery (Winter)

Figure 5.8: 4kWp Photovoltaic Installation Graphical Results (Summer and Winter)

5.5 New Battery Vs Used Battery with WattFuture

Last set of simulations were conducted to evaluate a more realistic scenario, where a completely new battery, with a SoH of 100% and no control by WF, is being compared to an used one, with 80% of SoH, that is being controlled by WattFuture.

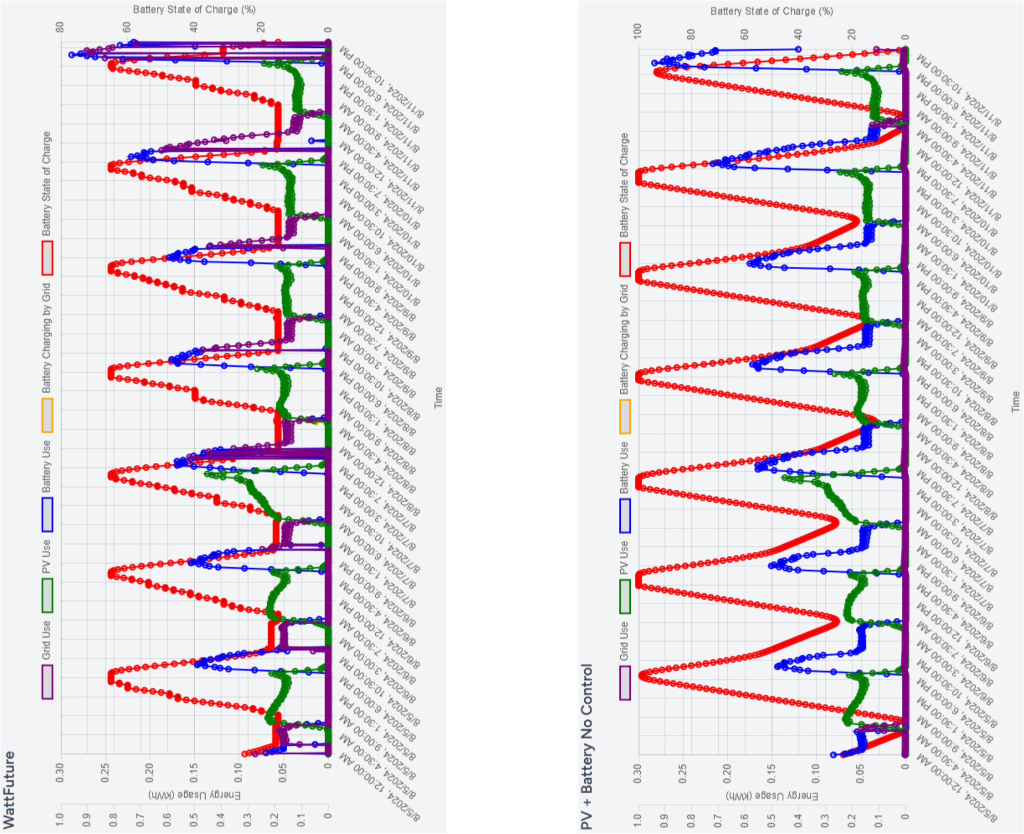
First experiment uses a 2kWp PV installation, costing 3200€, a new 5kWh battery costing 3500€ and 1500€ for the used. In this conditions, the PV installation weekly cost will be 2,46€, the used battery's weekly cost will be 1,68€ and the new battery's weekly cost will be 3,74€.

Table 5.14: 2kWp PV and 5kWh Battery Results (Summer and Winter)

Case Scenario	**Energy Cost (€/week)**		**Total Cost (€/week)**		**Reduction (%)**	
	Summer	**Winter**	**Summer**	**Winter**	**Summer**	**Winter**
Grid Only	7,77	14,70	7,77	14,70	0,00%	0,00%
With PV	2,93	11,76	5,39	14,22	30,61%	3,25%
PV + Battery	-0,64	9,81	5,56	16,01	28,43%	-8,92%
WattFuture	0,52	9,03	4,78	13,29	38,42%	9,56%

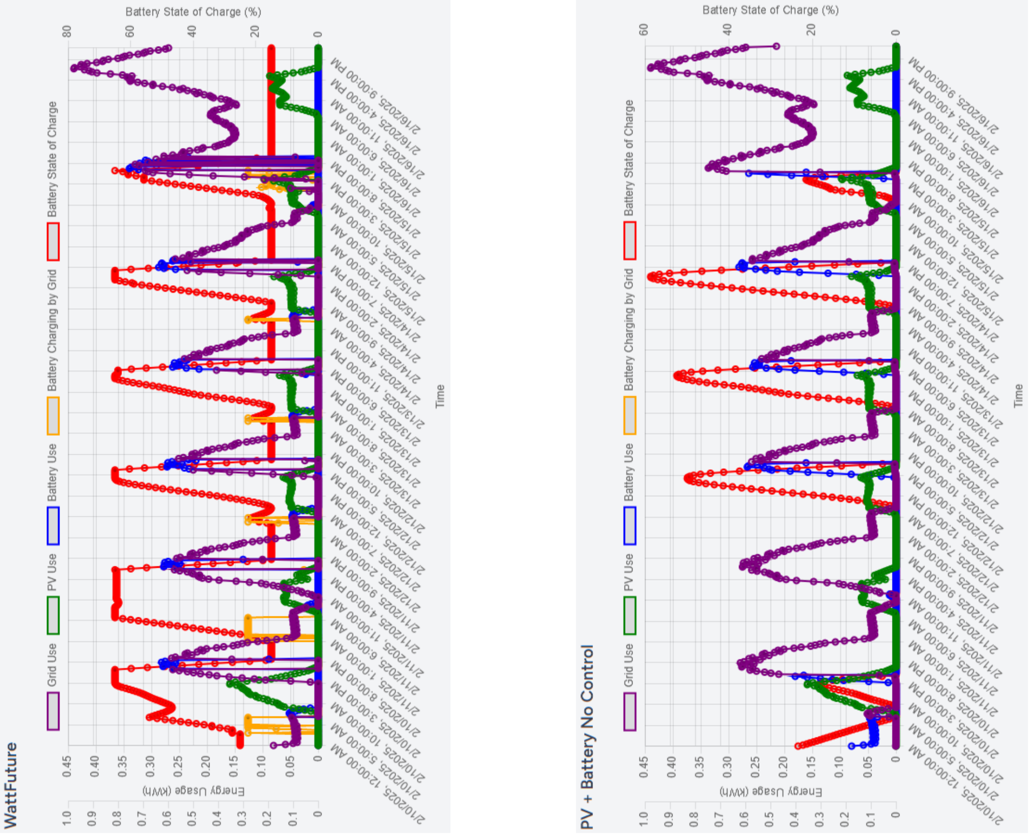
Table 5.14 shows the superiority of WattFuture's model again by outputting positive results with much lower investment. Using a new battery might seems beneficial during summer when looking at the Energy Cost column in table 5.14 (-0,64€), but the high initial investment makes the reduction percentage drop to 28,43%, almost half of the WattFuture's result.

The following graphs 5.9 reveals that the new battery manages to avoid grid consumption throughout the week during summer season since there is enough PV production to charge it. However, during winter, the battery never reaches 100%, which implies the use of energy from the grid.



(a) WattFuture (Summer)

(b) PV + Battery (Summer)



(c) WattFuture (Winter)

(d) PV + Battery (Winter)

Figure 5.9: 5kWh Battery with 2kWp Photovoltaic Graphical Results (Summer and Winter)

The second experiment was made to verify if a higher PV peak power will benefit the new battery scenario enough to compete with WattFuture's model. A 3kWp PV installation was now implemented with a cost of 4000€ and the 5kWh was maintained. In this conditions, the PV installation weekly cost will be 3,08€, the used battery's weekly cost will be 1,68€ and the new battery's weekly cost will be 3,74€.

Table 5.15: 3kWp PV and 5kWh Battery Results (Summer and Winter)

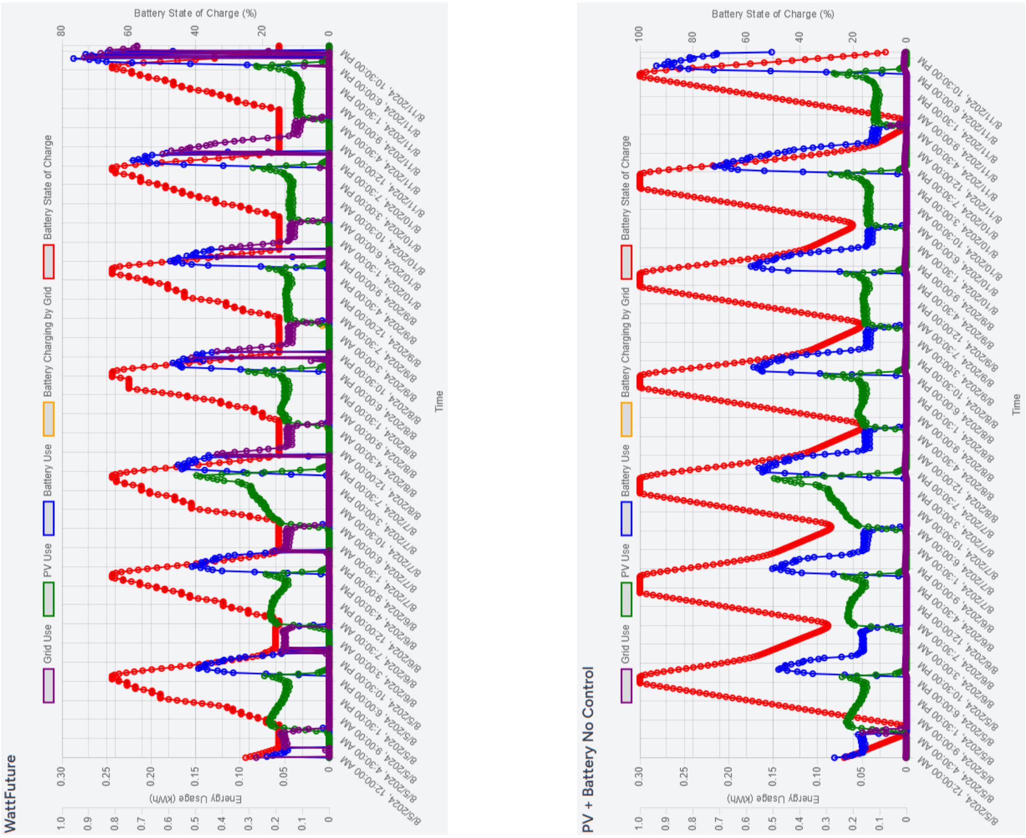
Case Scenario	**Energy Cost (€/week)**		**Total Cost (€/week)**		**Reduction (%)**	
	Summer	**Winter**	**Summer**	**Winter**	**Summer**	**Winter**
Grid Only	7,77	14,70	7,77	14,70	0,00%	0,00%
With PV	1,82	11,07	4,89	14,15	36,98%	3,76%
PV + Battery	-1,64	8,20	5,18	15,02	33,38%	-2,15%
WattFuture	-0,58	8,11	4,30	12,99	44,66%	11,63%

This experiment has shown better results for ever scenario as seen in table 5.15. The new battery scenario slowly reaches better numbers but still not as good as WattFuture's scenario and still worst than the scenario with PV only.

The following graphs 5.10 demonstrate that the scenario without WF won't improve much more since there is not a grid dependency throughout the week (except in the begin when the battery starts at 25%).

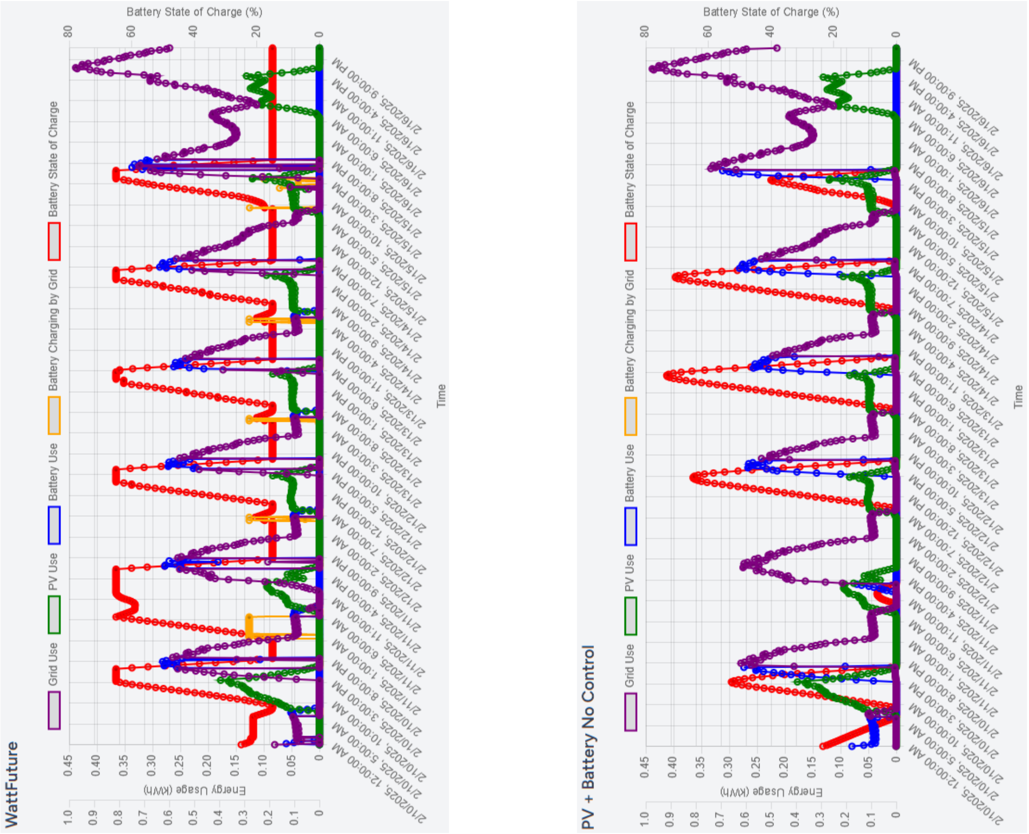
During winter, however, there is margin for improvements.

WattFuture's scenario seems to improve as peak power increases but this rising results might slow down as it reaches battery capacity limitations.



(a) WattFuture (Summer)

(b) PV + Battery (Summer)



(c) WattFuture (Winter)

(d) PV + Battery (Winter)

Figure 5.10: 5kWh Battery with 3kWp Photovoltaic Graphical Results (Summer and Winter)

As results seems to keep getting better as the PV peak power increases, a third experiment was conducted with a 4kWp PV installation that cost 4800€ and a new 5kWh battery costing 3500€. In this conditions, the PV installation weekly cost will be 3,69€, the used battery's weekly cost will be 1,68€ and the new battery's weekly cost will be 3,74€.

Additionally, an extra case scenario was included. This new scenario uses a new battery from 0-100% range with WattFuture's software. This way it's possible to verify that, even with WattFuture's model, the high price of a new battery makes the reduction percentage to drop lower than the scenario with an used battery.

Table 5.16: 4kWp PV and 5kWh Battery Results (Summer and Winter)

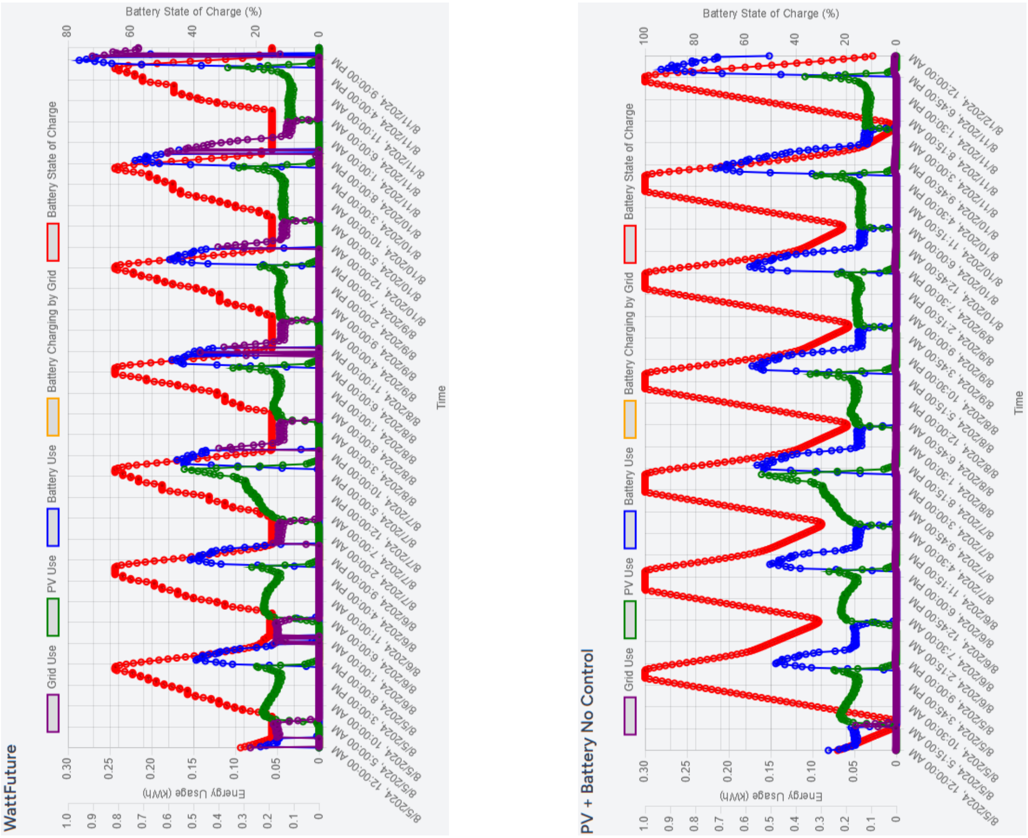
Case Scenario	**Energy Cost (€/week)**		**Total Cost (€/week)**		**Reduction (%)**	
	Summer	**Winter**	**Summer**	**Winter**	**Summer**	**Winter**
Grid Only	7,77	14,70	7,77	14,70	0,00%	0,00%
With PV	0,75	10,45	4,44	14,14	42,83%	3,79%
PV + Battery	-2,63	7,13	4,80	14,56	38,20%	0,94%
New w/WF	-2,65	6,05	4,78	13,48	38,46%	8,24%
Used w/WF	-1,63	7,42	3,87	12,92	50,25%	12,14%

As expected, table 5.16 reveals that all results have improved but the scenario with no control over the battery continues to underperform compared to the remaining scenarios. The high cost for the new battery makes it extremely difficult to get a return of investment.

This new scenario reveals that WF model makes a huge difference during winter when it's crucial to manage the energy available properly. It's noticeable that WF model doesn't have much impact during summer in the new battery because there is more than enough energy being produced and stored, leading to a grid independence.

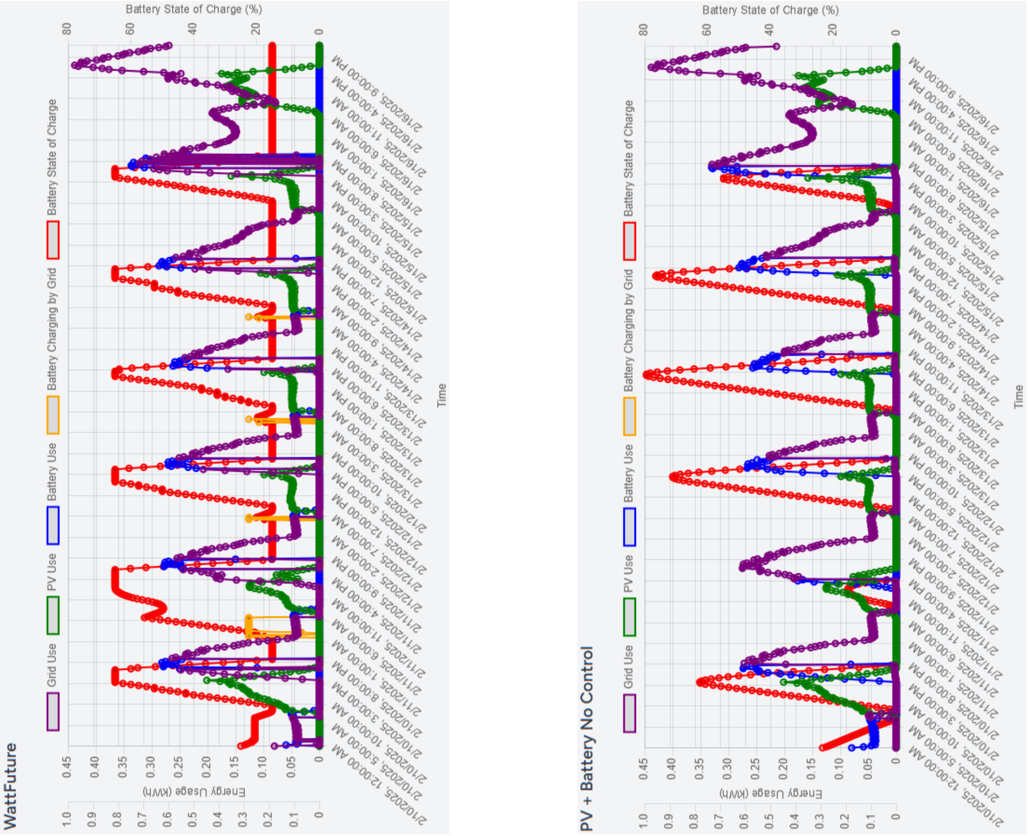
Even with WF improvement, the high investment in a new battery is dragging the reduction values down.

The following figures 5.11 help understanding the problem of a new battery with no control during winter.



(a) WattFuture (Summer)

(b) PV + Battery (Summer)



(c) WattFuture (Winter)

(d) PV + Battery (Winter)

Figure 5.11: 5kWh Battery with 4kWp Photovoltaic Graphical Results (Summer and Winter)

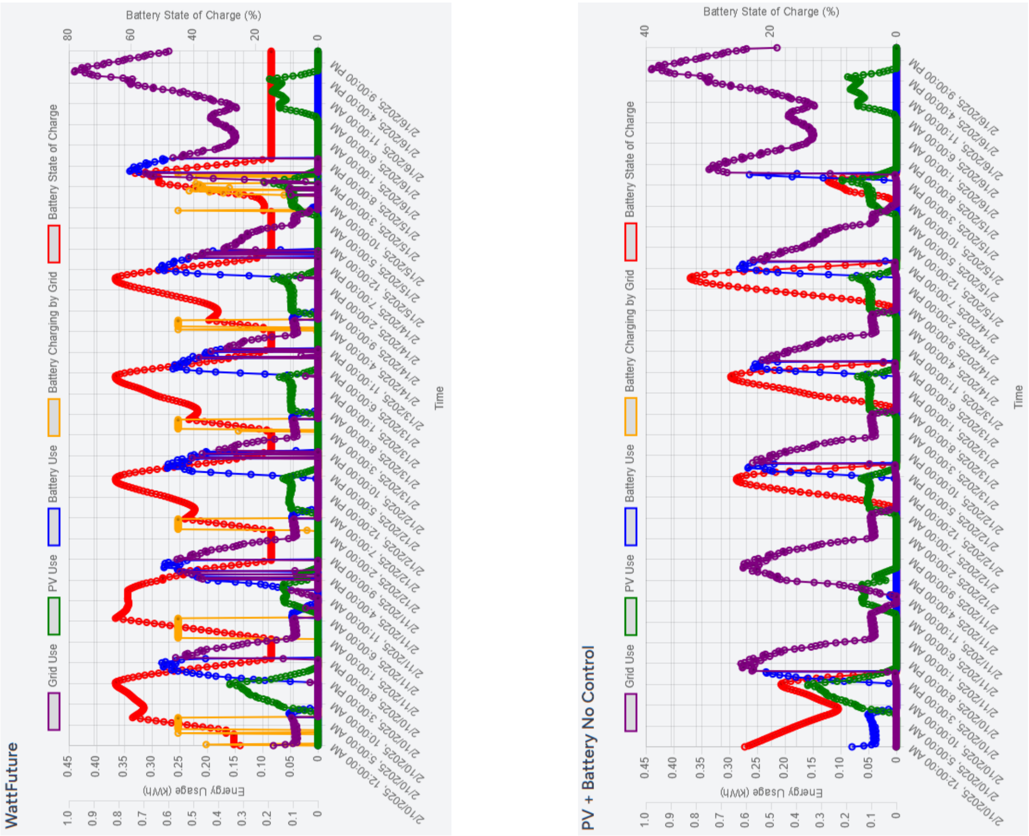
The next simulation was conducted to verify if a bigger battery capacity will be beneficial. A 10kWh battery, costing 7000€ when new and 2500€ when used, and a 2kWp PV installation was considered in this simulation. In this conditions, the PV installation weekly cost will be 2,46€, the used battery's weekly cost will be 3,00€ and the new battery's weekly cost will be 7,48€.

Table 5.17: 2kWp PV and 10kWh Battery Results (Summer and Winter)

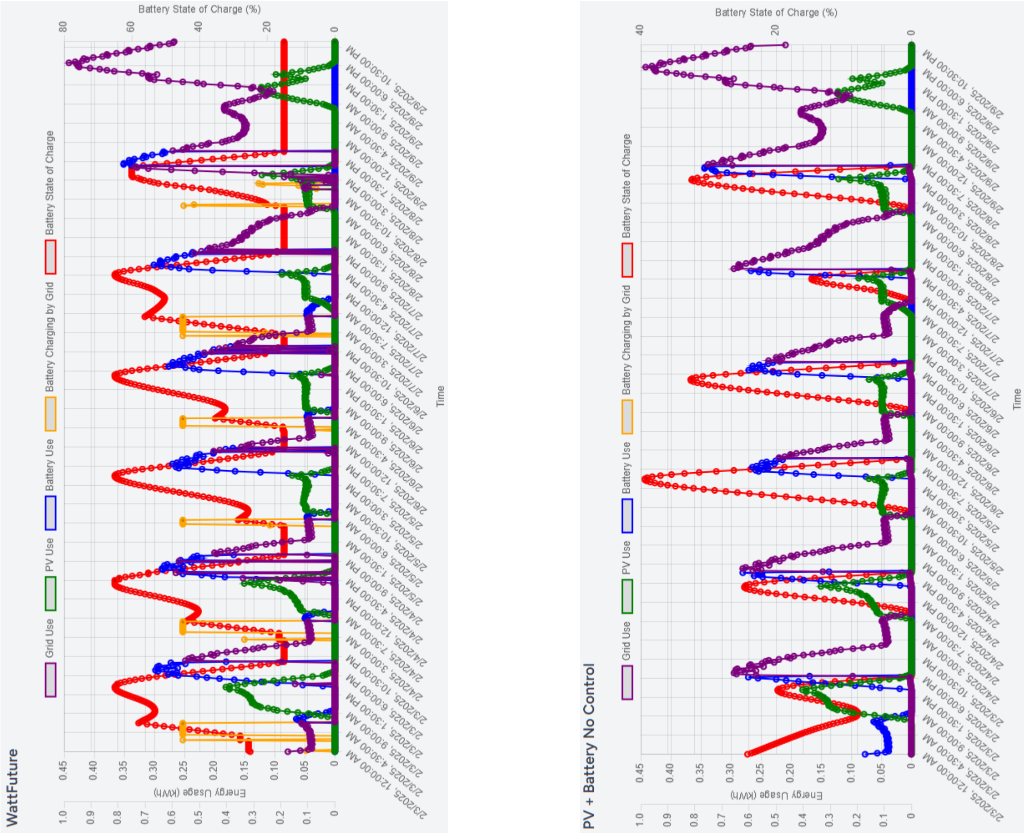
Case Scenario	**Energy Cost (€/week)**		**Total Cost (€/week)**		**Reduction (%)**	
	Summer	**Winter**	**Summer**	**Winter**	**Summer**	**Winter**
Grid Only	7,77	14,70	7,77	14,70	0,00%	0,00%
With PV	2,93	11,76	5,39	14,22	30,61%	3,25%
PV + Battery	-0,64	9,50	9,30	19,44	-19,69%	-32,25%
WattFuture	-0,64	7,94	4,83	13,41	37,88%	8,80%

Table 5.17 proves that a higher capacity battery in this household won't be beneficial as every reduction's metric dropped compared to the similar experiment 5.14 with a 5kWh.

The following figures 5.12 explain why the results dropped so much for the new battery. When using a 2kWp PV installation, there is not much energy being produced to fully charge the battery so it never reaches 100%.



(a) WattFuture (Summer) (b) PV + Battery (Summer)



(c) WattFuture (Winter) (d) PV + Battery (Winter)

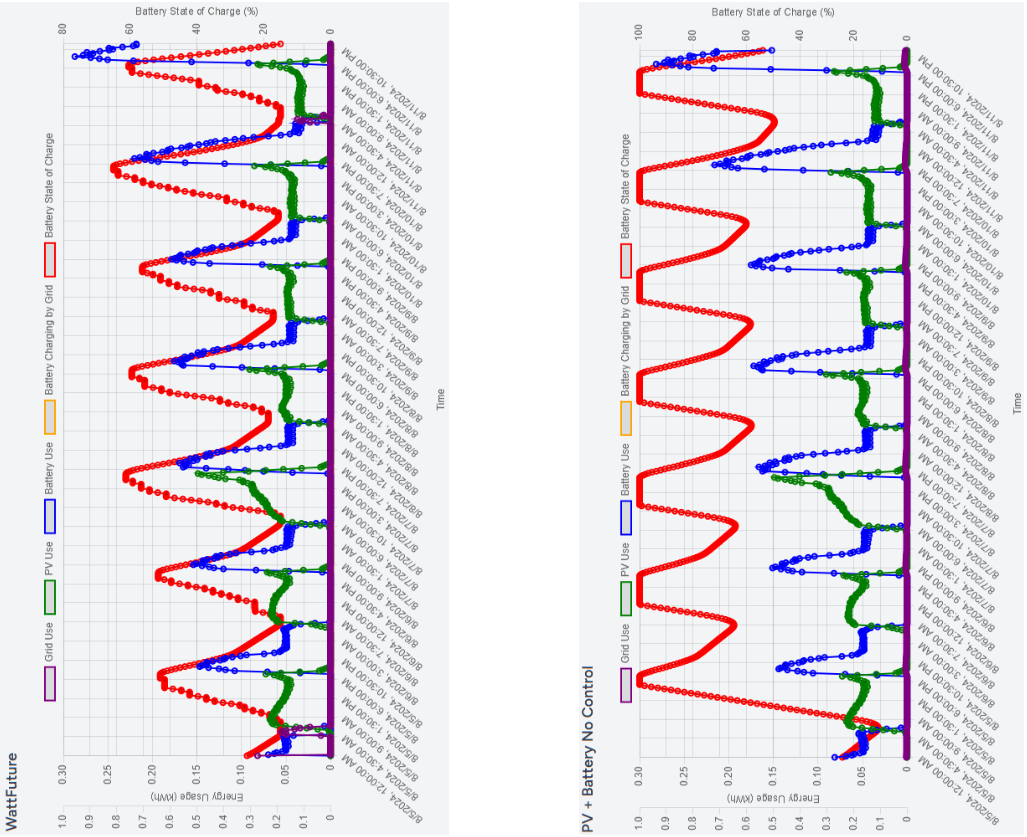
Figure 5.12: 10kWh Battery, 2kWp Photovoltaic Installation Results (Summer and Winter)

Last simulation increases the PV installation to 3kWp while keeping the 10kWh battery. In this conditions, the PV installation weekly cost will be 3,08€, the used battery's weekly cost will be 3,00€ and the new battery's weekly cost will be 7,48€.

Table 5.18: 3kWp PV and 10kWh Battery Results (Summer and Winter)

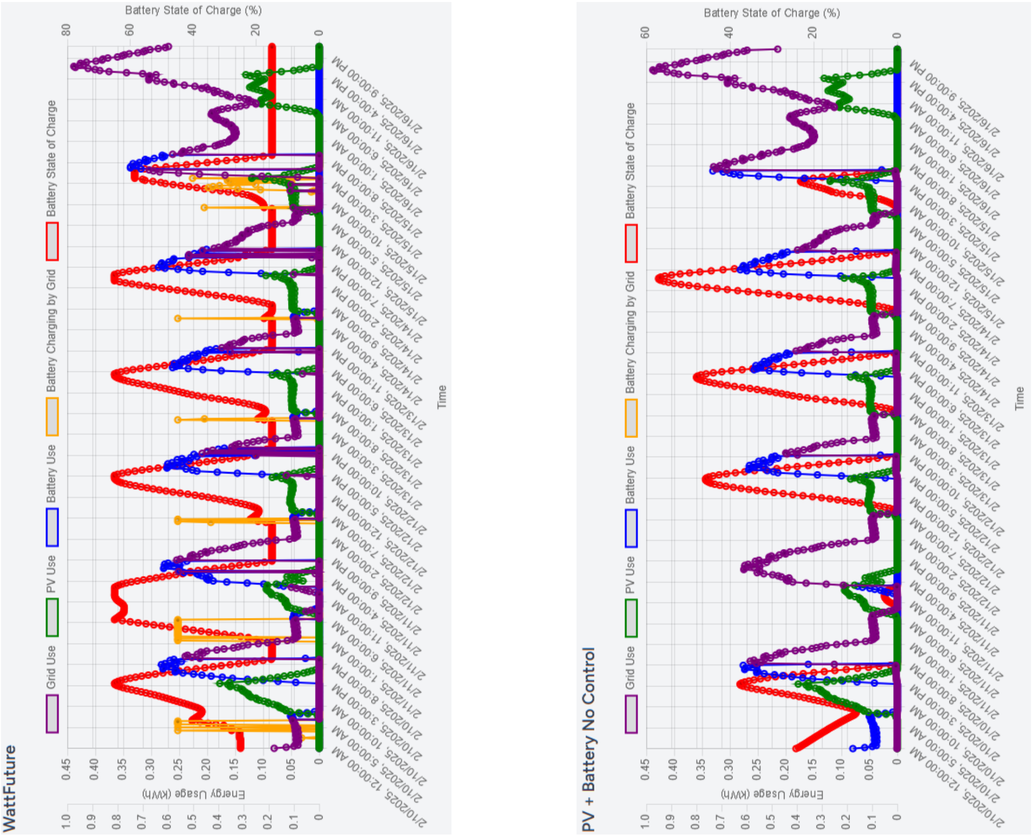
Case Scenario	**Energy Cost (€/week)**		**Total Cost (€/week)**		**Reduction (%)**	
	Summer	**Winter**	**Summer**	**Winter**	**Summer**	**Winter**
Grid Only	7,77	14,70	7,77	14,70	0,00%	0,00%
With PV	1,82	11,07	4,89	14,15	36,98%	3,76%
PV + Battery	-1,63	7,14	8,93	17,70	-14,87%	-20,38%
WattFuture	-1,63	6,48	4,45	12,56	42,71%	14,55%

Table 5.18 show better results from the previous experiment but still not as good as the similar experiment 5.15 with a 5kWh battery. Similar to the previous simulation, figures 5.13 suggests that this high capacity battery won't be properly used during winter without WattFuture.



(a) WattFuture (Summer)

(b) PV + Battery (Summer)



(c) WattFuture (Winter)

(d) PV + Battery (Winter)

Figure 5.13: 10kWh Battery, 3kWp Photovoltaic Installation Results (Summer and Winter)

Table 5.19 summarizes the performance of both new and second-life batteries across several PV configurations.

Table 5.19: New Battery vs Used Battery Summary Results (Summer and Winter)

Configuration (Table ref.)	**WF Reduction (%)**		**No Control Reduction (%)**		**PV Only Reduction (%)**	
	Summer	**Winter**	**Summer**	**Winter**	**Summer**	**Winter**
2 kWp + 5 kWh (5.14)	38.42%	9.56%	28.43%	-8.92%	30.61%	3.25%
3 kWp + 5 kWh (5.15)	44.66%	11.63%	33.38%	-2.15%	36.98%	3.76%
4 kWp + 5 kWh (5.16)	50.25%	12.14%	38.20%	0.94%	42.83%	3.79%
4 kWp + 5 kWh (New w/ WF) (5.16)	38.46%	8.24%	—	—	—	—
2 kWp + 10 kWh (5.17)	37.88%	8.80%	-19.69%	-32.25%	30.61%	3.25%
3 kWp + 10 kWh (5.18)	42.71%	14.55%	-14.87%	-20.38%	36.98%	3.76%

The results show that WattFuture consistently outperforms all other scenarios—even when paired with used batteries—achieving high reduction percentages with lower investments. Notably, new batteries without control often lead to negative returns due to their higher cost and lower flexibility in winter months.

In the majority of the simulations WattFuture's scenario is clearly superior, managing to achieve the highest reduction percentage with lower initial investment.

All simulations were conducted in the same household, with the same time interval to allow better and accurate comparisons.

Community's simulations weren't taken in consideration as results would be identical to the ones tested. It would be interesting to test WF model in a community with different households's patterns.

5.6 Global Analysis

All scenarios provided insights and helped to understand the real impact of WattFuture and its limitations. This section highlights all key notes of each experiment. Table 5.20 and table 5.21 groups all experiments conducted.

Table 5.20: Experiment Configuration Details

Experiment (Table ref.)	**PV Cap. (kWp)**	**Battery Type**	**Battery Cap. (kWh)**	**Battery Use Range (%)**		**Battery Lifetime (Years)**	
				w/WF	**no Control**	**Used**	**New**
1 (5.3)	1	Used	2.5	15-65	15-65	16	-
2 (5.4)	1	Used	5	15-65	15-65	16	-
3 (5.5)	1	Used	10	15-65	15-65	16	-
4 (5.7)	1	Used	5	15-95	15-95	8	-
5 (5.8)	1	Used/New	5	15-65	0-100	16	18
6 (5.10)	2	Used	5	15-65	15-65	16	-
7 (5.11)	3	Used	5	15-65	15-65	16	-
8 (5.12)	4	Used	5	15-65	15-65	16	-
9 (5.14)	2	Used/New	5	15-65	0-100	16	18
10 (5.15)	3	Used/New	5	15-65	0-100	16	18
11 (5.16)	4	Used/New	5	15-65	0-100	16	18
12 (5.17)	2	Used/New	10	15-65	0-100	16	18
13 (5.18)	3	Used/New	10	15-65	0-100	16	18

Table 5.21: Global Summary of All Simulations (Summer and Winter)

Experiment (Table ref.)	**WF Reduction (%)**		**No Control Reduction (%)**		**PV Only Reduction (%)**	
	Summer	**Winter**	**Summer**	**Winter**	**Summer**	**Winter**
1 (5.3)	27.79%	5.98%	26.64%	0.34%	26.53%	5.18%
2 (5.4)	34.60%	8.15%	33.83%	-3.34%	26.53%	5.18%
3 (5.5)	26.08%	6.85%	24.41%	-11.18%	26.53%	5.18%
4 (5.7)	20.67%	1.20%	19.00%	-13.97%	26.53%	5.18%
5 (5.8)	34.60%	8.15%	15.22%	-15.97%	26.53%	5.18%
6 (5.10)	38.42%	14.26%	38.30%	7.45%	30.59%	6.93%
7 (5.11)	44.66%	17.14%	44.53%	11.77%	36.98%	8.32%
8 (5.12)	50.25%	18.26%	50.25%	13.64%	42.83%	8.49%
9 (5.14)	38.42%	9.56%	28.43%	-8.92%	30.61%	3.25%
10 (5.15)	44.66%	11.63%	33.38%	-2.15%	36.98%	3.76%
11 (5.16)	50.25%	12.14%	38.20%	0.94%	42.83%	3.79%
11[1] (5.16)	38.46%	8.24%	—	—	—	—
12 (5.17)	37.88%	8.80%	-19.69%	-32.25%	30.61%	3.25%
13 (5.18)	42.71%	14.55%	-14.87%	-20.38%	36.98%	3.76%

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[1] New case scenario: A new battery controlled by WattFuture.

First, the main conclusions:

- WattFuture consistently outperformed all others configurations (except from experiment 5.7 where the limit range was set to 15-95% and led to an eight years battery lifetime).
- Bigger batteries did not always mean better cost reduction, as their initial investment is significantly higher (visible in experiments 5.5, 5.17 and 5.18).
- Higher PV installations increase savings but might reduce cost reduction if it produces too much energy that needs to be sold.
- Experiment (5.16) shows that an used battery with WF achieved better cost reductions over the new battery with WF.
- High investments and low energy savings result in negative reduction percentages, reaching higher weekly costs than the "Grid Only" case scenario.

These conclusions result from several trade-offs or limitations, such as:

- New batteries improved energy savings, but their high cost often made them less financially viable.
- Increasing PV power beyond 3kWp didn’t translate into significant winter gains.
- Winter was the biggest challenge for all setups.
- WattFuture offered the most consistent winter performance due to grid charging.

These simulations provided two of the best configuration for this household:

- The best reduction was obtained with a 4 kWp PV installation and an used 5 kWh battery with WF management, experiment 5.12.
- The configuration 5.10 with a 2 kWp PV installation and an used 5 kWh battery with WF management also provided a solid performance with a lower initial investment.

All experiments have shown advantages of using WattFuture over the scenario with no control. This advantage can escalate quickly if the household has the most adequate installation based on their needs.

Smart energy control is key to integrate batteries solutions.

6

Conclusions and Future Work

6.1 Conclusions

This thesis addresses a growing challenge in the energy sector: how to maximise the value of residential photovoltaic (PV) systems in the face of intermittent energy availability and high storage costs. While PV installations are becoming increasingly popular, their effectiveness is often limited by the intermittent nature of solar energy and the high upfront investment required for batteries.

Aiming to help the decarbonization process and faster Return of Investment (ROI), used batteries from electric vehicles were consider after reaching a state of health of 80%. This idea immediately drops the initial investment cost significantly. Additionally, controlling the battery between safe limits extends its lifetime and, consequentially, the system improves the return on investment (ROI) for users.

To get the most out of the battery, a predictive model was developed to optimize energy values by predicting energy production and energy consumption. After several tests, the ANN model was selected, even with LightGBM achieving slightly better performance in MSE and RMSE, because of its superior adaptability to deal with larger datasets and capture complex and non-linear behaviors. This predictions are crucial for WattFuture's model to allocate energy consumption in the best energy source possible, with the goal to reduce energy bill.

Instead of using only rules to control all energy transactions, WattFuture's model uses PuLP, which uses constraints and conditions that allow more freedom for the model to find the ideal energy source of each energy consumption. In section 5.1, from chapter 5, all results prove that that WattFuture's software has a major impact on the energy bill.

This WattFuture superiority comes from several key factors, such as the ability to control the battery charging during winter, storing energy for critical timezones or limiting the battery usage range to extend its lifetime, increasing ROI.

This work demonstrates the potential of combining second-life batteries with intelligent energy management to improve household energy efficiency.

It is with great satisfaction that this dissertation outcomes a positive result. Managing to combine two areas, energy and technology, to create a more sustainable way to manage energy consumption.

6.2 Limitations and Future Work

Throughout the tests of WattFuture's model, some aspects had to be assumed and can be improved in the future.

Starting with the predictive model, it can be improved over time when larger and real data is collected. Limited data was used and it may have caused some negative performance impact.

In an economic way, further work can bring more realistic and detailed prices, where tariffs, panels, batteries, etc. are constantly changing and estimated values had to be used in some aspects.

Another aspect that might need some work is the discharge and charging model. This dissertation has considered a linear behavior when charging or discharging a battery, which is not critical when maintaining a 15-65%, since the battery has a linear behavior in this range. However, using a full range won't be linear in the extremities. This non-linear behavior was not consider in this dissertation and should be consider in future works. This consideration would pronounce even more the superiority of WattFuture when controlling the battery between 15% and 65%.

This study relies on virtual simulations, which may not fully capture real-world inefficiencies. Future validation through experimental deployment in a real household or community setting would be beneficial. Unfortunately, this dissertation couldn't get this conditions and virtual simulations were conducted, providing virtual results that may or may not be totally accurate.

Would be interesting to study the WattFuture model performance in a community with different household's patterns.

Future works could verify the authenticity of this thesis.

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