# Optimal Battery Sizing and Control in a Stacked Revenue Model Incorporating a Renewable Energy Community

*Master's Thesis*

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# Optimal Battery Sizing and Control in a Stacked Revenue Model Incorporating a Renewable Energy Community

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**Abstract**

The transition to renewable energy sources requires advanced energy storage solutions to manage their intermittent nature. This thesis explores the feasibility of implementing Battery as a Service (BaaS) for a renewable energy community (RECs) setting, aiming to incorporate this model as part of an existing stacked revenue framework utilized by battery owners across various energy markets. By directly linking battery owners with energy communities, the study shows that renting out battery storage can eliminate intermediary overheads, thus providing financial benefits to both parties. The research addresses two main questions: developing a stacked revenue model for grid-connected batteries including energy communities, and comparing different battery sizing and control methods across various tariff schemes. The findings suggest that the proposed revenue model optimizes energy use and reduces costs for the community. This thesis contributes to the research field by presenting a viable economic model for integrating battery storage into decentralized energy communities.


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# Preface

This thesis marks the culmination of my long but unforgettable journey through the halls of Delft University of Technology. I will forever cherish the friends, the memories, and the knowledge I have gathered along the way. I cannot help but feel a little sadness as I write these final words, knowing that this important chapter of my life is about to come to an end. At the same time, I am hopeful, looking forward to the new chapter that is about to begin, knowing that I have grown tremendously over the past five years. As all good things must come to an end, so too must my journey at TU Delft.

I would like to express my deepest gratitude to all the people who have helped me during my academic journey. Without their support, this thesis would not have been possible.

First of all, I would like to thank my supervisor, Prof. Dr. Valentin Robu, who always found the time to discuss and guide me throughout my thesis. His valuable insights were vital to the success of this thesis, and for that, I am truly grateful. Furthermore, I extend my gratitude to Dr. Neil Yorke-Smith, not only for being part of my thesis committee but also for being an invaluable teacher throughout my journey. I would also like to thank Dr. Simon Tindemans for taking the time to review and grade my work as part of my thesis committee.

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My gratitude also extends to all the professors and lecturers who have inspired me along the way. I only hope to have the chance to inspire others in the same way.

Moreover, I would like to thank my parents, who have supported me, not only through this journey but throughout my life. They have always encouraged me to follow my passion and have shown me nothing but unconditional love, for which I will forever be grateful. I would also like to thank the rest of my family and friends, who have supported and inspired me and taught me many invaluable lessons.

Tudor Octavian Pocola<br>
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# Nomenclature

**Abbreviations**

| | |
|---|---|
| BaaS | Battery as a Service |
| BESS | Battery Energy Storage System |
| BMS | Battery Management System |
| BRP | Balance Responsible Party |
| CSC | Collective Self-Consumption |
| DoA | Degree of Autarky |
| DSO | Distribution System Operator |
| FFR | Fast Frequency Response |
| LP | Linear Programming |
| MILP | Mixed Integer Linear Programming |
| PV | Photovoltaic |
| REC | Renewable Energy Community |
| SC | Self-Consumption |
| SoC | State of Charge |
| SPT | Set-Point Tracking |
| TEP | Transmission Expansion Planning |
| TOU | Time of Use |
| TSO | Transmission System Operator |

**Parameters**

$\Delta t$ Time step duration

$\eta_c$ Charging efficiency of the battery

$\eta_d$ Discharging efficiency of the battery

$\eta_{cd}$ Round-trip efficiency of the battery

$\lambda^{capacity}$ Penalty for having an empty battery at the end of the day

$\lambda^{charging}$ Penalty for charging/discharging the battery

$\lambda^{max\_cycles}$ Maximum number of cycles allowed per day

$\tau_i^b$ Grid buying price at time $i$

$\tau_i^s$ Grid selling price at time $i$

$d_i$ Demand at time $i$

$g_i^{wind/solar}$ Generation at time $i$ from wind/solar sources

$p^{max}$ Maximum power of the battery

$SoC^{initial}$ Initial state of charge of the battery

$SoC^{max}$ Maximum state of charge of the battery

$SoC^{min}$ Minimum state of charge of the battery

**Subscripts and Sets**

$i$ Time index

$T$ Total number of time-steps

$wind/solar$ Wind or solar generation source

**Variables**

$e_i^b$ Energy imported from the grid at time $i$

$e_i^s$ Energy exported to the grid at time $i$

$p_i^{charge}$ Charging power of the battery at time $i$

$p_i^{discharge}$ Discharging power of the battery at time $i$

$SoC_i$ State of charge of the battery at time $i$

# Chapter 1

# Introduction

In recent years, there has been a significant increase in the adoption of renewable energy sources such as solar and wind power. This shift is driven by the global need to transition from fossil fuels to more sustainable energy solutions. According to the International Energy Agency (IEA), global renewable electricity capacity additions increased by nearly 50% in 2023, reaching 507 gigawatts (GW). This surge in renewable capacity is essential for meeting international climate targets, such as those set by the COP28 climate talks, which aim to triple renewable energy capacity by 2030 [33].

Research has shown that the integration of renewable energy sources into the power grid requires (advanced) energy storage solutions to manage the intermittent nature of renewable generation [3, 56]. Various studies have highlighted the importance of Battery Energy Storage Systems (BESS) in stabilizing the grid through ancillary services, such as supporting voltage and frequency regulation, and providing backup power during outages [7, 15, 36, 51, 60, 62]. The decreasing cost of lithium-ion batteries, combined with their high efficiency and rapid response times, has made them a preferred choice for energy storage.

In addition to individual battery systems, a notable development in the energy landscape is the emergence of energy communities. These communities consist of multiple prosumers (i.e. entities that both produce and consume energy) who combine their energy assets to optimize their energy use, reduce costs, and enhance the consumption of locally sourced renewable energy. Energy communities represent a decentralized approach to energy management, promoting local energy resilience and sustainability. This model not only supports the integration of renewable energy but also helps in mitigating the demand peaks and stabilizing the local grid [38, 40, 46, 61].

Despite the decreasing cost of lithium-ion batteries, they remain prohibitively expensive for most small to medium prosumers [17, 54]. Most owners or operators of grid-connected batteries use a stacked revenue model in ancillary markets, dividing the battery's total capacity among various revenue streams to maximize profits. This model often involves providing services such as frequency regulation, voltage support, and peak shaving. However, participating in these ancillary services requires specific certifications [36, 51]. These certifications ensure compliance with regulatory standards and guarantee the reliability of services provided, but obtaining them can be costly and time-consuming, presenting an additional barrier for small to medium prosumers to purchase and recoup their investment in battery storage systems.

The high costs and certification requirements mean that owning a large-scale battery is still reserved for those who can afford the initial investment and certification costs. Prosumers without storage capabilities must rely on the grid to export surplus energy and then reimport it later at a higher price. This dependency not only leads to higher energy bills for prosumers but also increases grid congestion, particularly as the number of households with energy production capabilities rises. This situation exacerbates the issues of centralization, as prosumers without battery storage rely heavily on the grid, which in turn depends on the services provided by battery owners.

This reliance is contrary to the decentralization trends aimed at making energy systems more locally resilient, i.e. able to balance generation/demand at a local level, and thus potentially, ease network congestion issues. By linking battery owners directly with energy communities, it would be possible to eliminate the middleman, creating financial benefits for both parties. Battery owners could rent out their battery storage to energy communities as part of their stacked revenue model. However, the potential feasibility of this solution has not been thoroughly studied, representing a gap in current research.

In this thesis, we will explore the feasibility of implementing Battery as a Service (BaaS) for energy communities. This study aims to incorporate this new revenue stream as part of the already existing stacked revenue model utilized by battery owners in the energy markets.

To achieve this, we will address the following research questions:

RQ1. How to develop a stacked revenue model for a grid-connected battery that includes an energy community?

(a) i.e. How to price the battery for different capacities?

(b) i.e. How to size the battery capacity for the different scenarios?

(c) i.e. How to size the energy generation?

RQ2. How different battery controls methods (Daily LP optimisation and Greedy heuristic real-time control) compare for different types of tariffs:

(a) a flat tariff scheme

(b) a dynamic tariff scheme

(c) the day-ahead market prices

The primary aim of the first research question is to evaluate the feasibility of the proposed revenue model. The study will primarily focus on the year 2023 in the Netherlands. The sub-questions aim to determine a fair renting price for both the community and the battery owner, identify the optimal battery size to be rented out to a community, and determine the optimal energy capacity that the community should install.

The second research question aims to analyze whether different battery control algorithms will significantly impact profitability. The study will evaluate three types of markets: flat tariffs, which are most common in the current market; dynamic tariffs, which have gained popularity recently; and market prices, typically not accessible by small and medium prosumers.

We hypothesize that renting out the battery will prove to be profitable because reliance on the energy grid incurs unnecessary overheads. By directly linking battery owners with energy communities, this overhead can be minimized, benefiting both parties and making the proposed model economically viable. Additionally, we start from the hypothesis that different battery control methods will significantly impact the final bill. Specifically, for flat tariffs, we expect the two control methods to perform similarly. However, in markets where prices fluctuate, we foresee that the linear optimization method will demonstrate superior performance.

The structure of this thesis begins with the Background chapter, which provides an overview of battery energy storage systems and the concept of energy communities. Following this, the Related Work chapter reviews existing literature and previous studies relevant to BEESs and energy communities, setting the stage for our research. The Methodology chapter explains the research methods and models used in the study, detailing how data was gathered and analyzed. In the Experimental Results chapter, we present and discuss the findings from our experiments. The Discussion chapter interprets these results, exploring their implications and how they relate to our hypotheses. Finally, the Conclusion and Future Work chapter summarizes the thesis's main findings, discusses their importance, and proposes directions for future research.

In this thesis, we will investigate a community of 200 households, which share a small wind turbine. The battery owner in our study will be GIGA Storage, a company that operates multiple BESS systems across the Netherlands and currently generates profit through a stacked revenue model in the ancillary markets. The analysis will try to identify the scenarios which are profitability for both parties, incentivizing them to participate in the proposed model.

# Chapter 2

# Background

The global energy landscape is currently undergoing a significant transformation, driven by the urgent need to transition to renewable energy sources. In 2023, global renewable capacity additions set a new record for the 22nd consecutive year [33]. This shift is characterized by increasing investments in renewable energy capacity, advancements in energy storage technologies, and the rise of decentralized energy communities. This chapter provides background information on key components of this transition, including battery energy storage systems and their pivotal role, the activities of GIGA Storage, the day-ahead and imbalance markets, and the emerging concept of energy communities. Understanding these elements may help readers gain a better understanding of the context analyzed in this thesis.

## 2.1 Energy Storage Systems

In 2021, despite a decline in demand for all other fuels, renewable energy sources increased by 3% compared to 2020, accounting for 290 GW of added capacity [32]. The IEA estimated in 2021 that the installed capacity would reach 352.3 GW by 2023. However, by 2023, the newly added capacity had already reached 510 GW [33]. This growth is expected to accelerate in the coming years, with renewable capacity anticipated to surpass coal by 2025, becoming the largest source of electricity generation. By 2028, it is expected that renewable energy sources will account for over 42% of global electricity generation, with wind and solar PV contributing 25% of this total. In 2021, the IEA forecasted that global renewable electricity capacity would reach over 4800 GW by 2026 [32]. In 2023, this estimate was revised upwards to 5900 GW. Although the installed capacity has exceeded expectations, we are still not on track to meet the COP28 targets of tripling global renewable capacity by 2030.

As the share of renewable energy sources in the global energy mix increases, so does the importance of reliable energy storage solutions. Renewable energy sources, such as solar and wind, have inherently variable outputs, depending on weather conditions, time of day, and season. This variability necessitates the development and implementation of efficient energy storage solutions to ensure a reliable and constant energy supply [3, 56].

Various energy storage solutions have been developed to meet this need, including pumped hydro, compressed air, flywheel energy storage, hydrogen technologies, and batteries [37]. Among these, lithium-ion Battery Energy Storage Systems (BESSs) have become particularly advantageous due to their rapid response times, high power throughput, and high round-trip efficiency. However, the cost of these batteries has been a significant barrier to early adoption. Despite this, there has been a notable decrease in recent years, making them more economically viable [43]. A white paper by the Solar Energy Industry Association (SEIA) from November 2023 projects that demand for battery storage systems in the United States will increase sixfold over the next six years. Globally, the SEIA anticipates that the demand for BESSs, primarily used in renewable energy projects, will grow from 60 GWh in 2022 to approximately 840 GWh by 2030 [3].

## 2.2 Battery Energy Storage System as a Service

BESSs have become a critical component of the energy sector, facilitating the integration of renewable energy sources into the grid. BESS owners can support this integration by participating in either the wholesale market or in ancillary energy markets, providing services such as voltage support, frequency regulation, black-start, congestion relief, peak-shaving, and power smoothing [51, 7, 62, 60]. These services are important for maintaining grid stability and ensuring a balance between supply and demand.

The economic viability of BESSs in these markets can be greatly improved by employing a stacked revenue model. This model allows BESS owners to provide multiple services simultaneously, thereby unlocking multiple revenue streams [57]. The key challenge of this model is determining the optimal times for charging and discharging the battery in response to shifting market prices, while also minimizing battery degradation [8]. To effectively engage the wholesale and ancillary markets with a stacked revenue model, BESS owners must deploy competitive and efficient control algorithms that consider not only the dynamics of the energy market but also any legislative regulations that might be present.

## 2.3 GIGA Storage

GIGA Storage[1] is an Amsterdam-based start-up that has realized some of the largest grid-connected battery projects in the Netherlands. Specifically, it has completed two BESSs: Rhino, with a rating of 12MW/7.5MWh, and Buffalo, rated at 25MW/48MWh. They have three additional projects under development in the Netherlands and two in Belgium. The largest project in the Netherlands, Leopard, is rated at 300MW/1,200MWh. All of GIGA Storage's systems use lithium-ion batteries, differing only in their cathode materials. GIGA Storage generates revenue by operating its batteries in the frequency regulation market, day-ahead market, and imbalance market. They also have contracts with local renewable energy producers to import energy at imbalance prices, allowing them to import energy at market prices without incurring transport costs.

The starting point of this thesis project is to explore the feasibility of adding ”Battery as a Service” for energy communities to their stacked revenue model.

[1] https://giga-storage.com/

## 2.4 Electricity markets

The two types of electricity markets are the wholesale markets and the ancillary markets. In the wholesale markets, the primary product is energy, which is bought and sold at varying prices. The four main types of wholesale markets are the Forward Market, the Day-Ahead Market, the Intraday Market, and the Imbalance Market, each operating through different mechanisms. Revenue for BESS owners in these markets is derived from price arbitrage, where energy is purchased at low prices and sold at higher prices, thus profiting from the price differential.

In contrast, the ancillary markets compensate participants for providing essential support to maintain smooth grid operations. Common ancillary services that BESSs participate in include the Frequency Containment Reserve (FCR) and the automatic Frequency Restoration Reserve (aFRR). FCR helps maintain grid stability by balancing short-term frequency deviations, while the aFRR helps restore the system frequency to its nominal value after a disturbance. Participants who provide these services receive a flat fee for being on standby. If a disturbance occurs, they will have to provide the agreed-upon service, receiving extra compensation in the process. This setup is advantageous for BESS owners as it allows them to generate revenue by being on call, resulting in less battery usage and prolonging the battery's lifetime.

Although ancillary markets have traditionally been the most common application for BESS, GIGA Storage has observed a decline in profitability from these markets. Consequently, they have shifted their revenue model towards price arbitrage in the Day-Ahead and Imbalance Markets. This thesis focuses on analyzing the day-ahead market and the imbalance market, both managed by TenneT in the Netherlands [59]. These markets are accessible only to Balance Responsible Parties (BRPs), who are responsible for planning daily electricity transactions and ensuring that the grid remains balanced, thus preventing both overload and underload conditions [25].

In the day-ahead market, participants can buy and sell electricity in a pan-European auction for the 24 hours of the next day in hourly blocks. Prices in this market are set 12 hours before it opens, with the electricity price and volume for each hour determined by the intersection of demand and supply. This price is then paid or received by all successful auction participants. The day-ahead market, organized with a relatively short time horizon of 12 hours before delivery and featuring a single clearing price, accurately reflects the value of electricity at different hours. Consequently, this clearing price is often referred to as "the electricity price". In Europe, the price is determined per bidding zone, typically aligning with national borders [59, 30].

The imbalance market allows parties to voluntarily help maintain system balance. This market becomes relevant when unscheduled actions are taken by energy parties. When this occurs, TenneT offers the current imbalance market price for their energy. During periods of excess generation, prices are lowered to motivate consumers to reduce consumption. Conversely, in the case of a generation deficit, prices increase to incentivize consumers to boost consumption or promote energy generation [59, 55].

## 2.5 Energy Communities

In recent years, there has been a significant shift towards the decentralization of the energy grid, driven by the local production and consumption of energy within energy communities. This decentralization plays a vital role in our transition towards renewable energy sources, increasing flexibility, efficiency, and sustainability in the energy market [27]. This is needed as the current centralized models have been too slow to adapt to the transition towards renewable energy sources and the progress made so far has been insufficient [9]. This transition is also linked to the democratization of energy, where individuals or communities have more control over their own production and consumption of energy.

This shift is illustrated by the recent rise of prosumer communities [45], where individuals both produce and consume the energy within the community, through decentralized systems that utilize renewable power sources, such as solar or wind. This shift not only challenges the traditional centralized models, but also opens up new opportunities for peer-to-peer trading [48], smart grids [19], and blockchain technologies [23], further increasing the resilience and sustainability of the energy systems.

# Chapter 3

# Related Work

To situate this thesis within the relevant research fields, this chapter presents a comprehensive review of the literature. The review is organized into three main sections aligned with the research questions: Battery Energy Storage Systems (BESS) as a service, Renewable Energy Communities (REC), and Optimal Battery Control.

The first section explores the various applications of BESS identified in the literature. It highlights that most BESS are deployed using a stacked revenue model, participating in both grid services and ancillary markets. The second section examines the emerging trend of RECs, discussing the critical role of BESS in these communities and the configurations under which they are implemented. The first two sections focus more on techno-economic analysis and policy-making aspects of the problem. The final section delves into general control methods for BESS, focusing on technical perspectives and control strategies, and examining studies that address these issues from a more theoretical standpoint.

By clustering the literature in this manner, this review aims to provide a structured understanding of the current state of research and identify gaps that this thesis seeks to address. We will see that the problem of Battery as a Service (BaaS) for energy communities has not been thoroughly studied, if at all. It has merely been proposed as a future research direction in some studies, indicating a clear gap in the literature. This thesis aims to fill that gap by exploring the feasibility and potential benefits of implementing BaaS within energy communities.

## 3.1 BESS as a service

Kooshknow and Davis [36] present a map of single-use cases for BESS in the Netherlands energy market to make them profitable. Their goal was to find possible applications for different actors in the Dutch electricity markets, such as transmission system operators (TSO), distribution system operators (DSO), power generation companies, energy traders, energy suppliers, energy retailers, and end consumers. They find that the BESSs are mainly used in the reserve market, but they expect this to change, as the need for flexibility and energy storage will increase.

Marnell et al. [35] review the viability of transmission-scale BESSs by examining various battery technologies, operational costs, and potential revenue streams for owners. Identified revenue streams include ancillary services such as voltage support, black start, and reserves. Additionally, the review examines revenue opportunities through price arbitrage and congestion relief. While not extensively analyzed, islanding support is noted as a potential revenue stream, aligning with decentralization trends. The review highlights the significance of a stacked revenue model, where a joint optimization function allows for the optimal scheduling of BESS to maximize revenue.

Ramos et al [54] identified and analyzed multiple business scenarios for BESS as a service by examining 10 battery installations in Finland, which provide various services to the energy market. They identified three main categories of services that can be provided by BESS, one of which was BESS as a service for end users, or communities. The focus of their study was to identify the gap between the available research and the challenges that arise when implementing those solutions in practice, through interviews with the relevant stakeholders. One of the relevant problems for energy communities is that the price of BEES is still too high to be considered a competitive solution, without a stacked revenue model.

Prakash et al. conducted a literature review to examine the current status, challenges, and future directions of BESSs for ancillary services in the electrical distribution grid. Using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework, the review systematically identified and analyzed 115 papers published from 2010 to 2022. The review highlights three critical applications where BESS can significantly stabilize and optimize grid operations: frequency regulation, voltage support, and peak shaving. The authors also identified the barriers to BESS deployment and proposed potential future research directions to address these challenges. [51].

Biggins et al. [14] analyze the optimization of BESSs for simultaneous participation in multiple energy markets, including ancillary services required worldwide. The authors propose a novel approach to optimize a stacked revenue model between the frequency regulation (FR) market and price arbitrage. They first predict the likelihood of their battery being accepted to provide frequency regulation. This probability is then incorporated into a mixed-integer linear programming (MILP) optimization model, which generates a schedule that accounts for this risk. The results show that FFR is a larger source of revenue than arbitrage for battery storage. However, they also demonstrate that performing arbitrage within a small, risk-constrained band is both economical and feasible in real-time operations.

Castillo et al. [15] addresses the integration of renewable energy through the provision of ancillary services, by battery energy storage systems (BESS). The paper examines various control strategies and market participation rules that optimize BESS performance in ancillary markets. It also addresses the technical challenges of improving BESS efficiency and reliability. The paper highlights how BESS can mitigate the power quality issues associated with the intermittent nature of renewable energy sources by providing a smooth and controlled output. The review covers a wide range of BESS applications, including frequency regulation, voltage support, energy arbitrage, peak shaving, load smoothing, and black start capabilities. The authors emphasize the need for advanced control strategies to ensure that BESS can respond quickly to frequency fluctuations and voltage disturbances, thereby maintaining grid stability. The review also notes the importance of optimizing

BESS sizing and location to maximize economic benefits and enhance grid reliability.

Gulotta et al. [28] review the integration of distributed energy resources (DERs), including BESSs, into ancillary service markets. It highlights the transition from centralized, fossil fuel-based generation to decentralized, renewable energy-based models, where DERs provide essential regulation services for grid stability. The paper discusses various strategies and regulatory frameworks that enable DERs to effectively participate in both wholesale and local markets, including peer-to-peer and decentralized setups. These local markets are usually managed by distribution system operators (DSOs) to facilitate prosumer participation. Emphasizing the decentralization trend, the study underscores the need for sophisticated control and coordination mechanisms as energy generation increasingly shifts to small, distributed power plants. The review highlights the importance of DERs in enhancing grid reliability and the economic benefits of including BESS in ancillary markets.

## 3.2 Renewable Energy Communities

Davis and Hiralal [17] evaluate the economic feasibility of individual prosumers from the UK buying their own batteries and using them to either keep their consumption flat or to displace all of the daytime electricity demands to the nighttime when prices are lower. Both use cases were deemed not economically feasible without government subsidies, as the cost of the battery, inverter, and installation could not be recouped. The authors suggest battery as a service as a possible alternative, instead of the communities owning these assets themselves.

Guetes et al. [27] explored the restructuring of traditional power systems, due to the recent shift towards a decentralized model, where prosumers have their own generation and storage capabilities. The main contribution is a linear optimization model for incorporating BESS into energy communities, aimed at increasing community income while taking the battery degradation into account. Furthermore, the feasibility of different use cases is evaluated using social welfare and fairness indicators. They have shown that when the BESS is inserted as an independent agent into a community it improves community satisfaction while also increasing the social welfare of the market.

Aranzabal et al. [11] presents a new approach towards maximizing the economic revenue that a BESS can provide within a REC. The study outlines a strategy for scheduling BESS operations, by considering RECs as virtual microgrids that are allowed to participate in ancillary markets such as automatic frequency restoration reserves (aFRR). The authors introduce a three-step control strategy for BESS: initially, a machine learning algorithm is used for predicting the microgrid load and generation; secondly, a mixed integer linear programming (MILP) algorithm is used for creating an optimal schedule based on the forecasted data; and lastly, a decision-tree algorithm used to adjust the schedule in real-time based on the actual data. They show that the proposed strategy can be profitable in some use cases and that it can be easily scaled for different configurations or scenarios.

Belmar et al. [13] model different design configurations of energy communities in Lisbon, Portugal, focusing on assessing their economic and environmental impacts within various local energy market setups. Their research identifies that in the most favorable scenario, prosumers equipped with a combination of photovoltaic (PV) systems and BESSs achieve the highest cost savings, with residential prosumers saving up to 53%. This scenario assumes 100% participation rates and decreased investment costs for both PV and BESS. In a more realistic scenario, the study suggests that savings could reach up to 20%. The study concludes that the outcomes for energy communities are highly dependent on the specific configurations used in the modeling process.

Pasqui et al. [47] presents a techno-economic analysis of a REC in Florence, focusing on the integration of battery management systems (BMS). It evaluates the performance and benefits of four different BMS configurations: no battery (PVrec), standard (StBMS), smart (SmBMS), and optimal (OpBMS). The study finds that the SmBMS, which uses real-time data monitoring, enhances collective self-consumption (CSC) and provides greater energy independence from the national grid, albeit with a slight economic disadvantage for prosumers. In contrast, the OpBMS, based on perfect foresight of production and demand, optimizes energy distribution and maximizes community profits but is impractical for real-world implementation. The paper emphasizes the role of government incentives and third-party companies in managing the economic feasibility and operational efficiency of RECs, proposing that SmBMS is a practical and beneficial solution for maximizing CSC and supporting sustainable energy practices within energy communities.

Ahmed et al. [6] offers a comprehensive review of RECs, exploring their concepts and benefits in enhancing energy independence and resilience. The authors highlight the importance of Energy Storage Systems (ESSs), such as batteries, as crucial components of these communities. However, challenges like high initial costs and potential technical issues with battery maintenance and lifespan are noted as disadvantages. Despite these obstacles, electrical energy storage remains particularly promising among potential solutions [16], emerging as the most cost-effective in the current economic climate, although they have a higher environmental impact compared to other technologies [29]. The review also addresses the progress and challenges faced by RECs, providing recommendations for policymakers and stakeholders to promote sustainable, community-driven energy systems.

## 3.3 Optimal Battery Control

There has been an increase in recent years in modeling interest in Battery Energy Storage Systems (BESS) as a linear set of constraints [58]. These models provide a fast and clear way of analyzing the optimal behavior of BESS across various problems. However, LP models lack an explicit formulation that accounts for mutually exclusive operations, such as charging and discharging. Additional constraints can be added to address this issue, but they significantly slow down the model [12]. This occurs because the added constraints contain binary variables, converting the model into a mixed-integer linear programming (MILP) model, which is considerably slower. Zhao et al. [63] suggested that the binary representation can be omitted if the battery's round-trip efficiency is less than one. However, Jose et al. [12] disproved this by counter-example.

A more recent study by Pozo [50] directly tackles this problem by analyzing the most useful linear BESS models and their limitations. The study investigates one MILP model and four LP models in the context of two classical power system problems: set-point tracking (SPT) and transmission expansion planning (TEP). The first two models analyzed are **Exact-MILP** and **Simp-LP**, both well-known and widely used in the techno-economic analysis of power systems, with **Simp-LP** being a simplified version of **Exact-MILP**. The third model, **NaAl-LP**, introduced by Nazir and Almassalkhi [41], always produces a feasible charging schedule with respect to the state of energy limits. The fourth model, **Relax-LP**, is a relaxation of the **Exact-MILP** model, and the fifth model, **Extn-LP**, proposed by Pozo, is the closest to the MILP formulation. The paper evaluates these models through the SPT and TEP problems, finding that only the **Exact-MILP** model avoids simultaneous charging and discharging, although it is significantly slower. In the SPT problem, the relaxed LP models tend to overestimate the objective function, with **Simp-LP** being the most overoptimistic at 15%. For the TEP problem, the differences between the objective functions of the models are small, making them irrelevant for practical long-term planning decisions.

Qin et al. (2016) [52] formulate the problem of optimal operation of energy storage systems under uncertainty as a stochastic control problem with general cost functions. They propose a simple yet effective algorithm called the Online Modified Greedy (OMG) algorithm. They demonstrate that the OMG algorithm has sub-optimal control when compared to the optimal cost of the problem. However, they prove that this sub-optimality is bound by a function of the system parameters. The bound on this sub-optimality is easily computable, making the algorithm practical and theoretically sound for evaluating the performance of other heuristic algorithms. Additionally, they extended the algorithm to a distributed setting [53], which allows for networked storage operation under uncertainty, enhancing its scalability and applicability in larger, more complex systems.

# Chapter 4

# Methodology

The methodology section of this thesis details the approach employed to investigate the feasibility of a grid-connected battery owner renting out a portion of their Battery Energy Storage System (BESS) capacity to a Renewable Energy Community (REC). The study focuses on the applicability of this model within the Dutch energy market. For the simulation, the Rhino system, owned by GIGA Storage and rated at 12MW/7.5MWh, was utilized. The research is structured around two primary components: community simulation and spot market simulation. These simulations allocate part of the battery for community use and part for company operations, running over a full year and utilizing historical data from 2023 wherever possible.

In the community simulation, two distinct control strategies are employed: a model-free greedy algorithm and a linear optimization model. The greedy algorithm prioritizes immediate actions based on the current state, while the linear optimization model plans for a full day. For the market simulation, a similar but simpler linear model is used to optimize the optimize the daily charging and discharging schedule of the battery.

Additionally, this methodology covers data gathering and preprocessing, incorporating real-world demand and generation data alongside market prices to ensure the simulations are grounded in realistic scenarios. This approach allows for an accurate assessment of the proposed model.

## 4.1 Community Simulation

For the community simulation, we will employ two distinct control strategies, each with a different event horizon. The first approach utilizes a model-free greedy algorithm, taking the optimal action at each given step based solely on the current state. The second approach employs a linear optimization model with a one-day event horizon, determining the optimal schedule for the entire day. This model runs independently for each day, requiring more input data at runtime, some of which must be estimated (e.g., demand and generation curves). While these estimations are not the primary focus of this study, their feasibility is discussed in the Discussion section. The following subsections will delve into the specifics of each implemented approach.

### 4.1.1 Greedy Model

The most straightforward control algorithm for battery management, which requires no information about future generation, demand, or prices, is a model-free greedy algorithm. The formulation proposed by Norbu et al. [42] was adapted for use in this thesis. This greedy algorithm prioritizes the use of the battery over the grid whenever possible. It is termed "model-free" because it operates solely based on the current state without accounting for future conditions. Specifically, in scenarios of excess energy generation, the algorithm will charge the battery first, resorting to exporting energy only if the excess power exceeds the battery's specifications or if the battery lacks sufficient capacity to store all the generated energy. Conversely, during energy deficits, the algorithm will discharge the battery first, importing energy only if the required power surpasses the battery's maximum power rating or if the stored energy is insufficient to cover the deficit. This algorithm is optimal for a flat import and export tariff structure, assuming the import cost exceeds the export cost. The formal definition of the algorithm is given as Algorithm 1.

**Algorithm 1** Model-Free Battery Control Algorithm

**Require:** Generation: $g_i^{wind/solar}$, Demand: $d_i$, Grid Price: $\tau_i^b$, $\tau_i^s$
**Require:** Battery Specifications: $\eta^c$, $\eta^d$, $SoC^{initial}$, $SoC^{max}$, $SoC^{min}$, $p^{bat,max}$
**Ensure:** State of Charge $SoC_i$, Exported Energy $e_i^s$, Imported Energy $e_i^b$
1: Initialize $SoC_0 \leftarrow SoC^{initial}$
2: Initialize $T \leftarrow |g^{wind/solar}|$ ▷ Number of timesteps
3: **for** $i \leftarrow 1, T$ **do**
4:     **if** $g_i^{wind/solar} \geq d_i$ **then** ▷ Excess Energy Scenario
5:         $p_i^{charge} \leftarrow \min\left(g_i^{wind/solar} - d_i, p^{max}\right)$
6:         $SoC^{change} \leftarrow \min\left(p_i^{charge} \cdot \Delta t \cdot \eta^c, SoC^{max} - SoC_{i-1}\right)$
7:         $SoC_i \leftarrow SoC_{i-1} + SoC^{change}$
8:         $e_i^s \leftarrow (g_i^{wind/solar} - d_i) \cdot \Delta t + SoC^{change}/\eta^c$
9:     **else** ▷ Energy Deficit Scenario
10:         $p_i^{discharge} \leftarrow \min\left(d_i - g_i^{wind/solar}, p^{max}\right)$
11:         $SoC^{change} \leftarrow \min\left(p_i^{discharge} \cdot \Delta t/\eta^d, SoC_{i-1} - SoC^{min}\right)$
12:         $SoC_i \leftarrow SoC_{i-1} - SoC^{change}$
13:         $e_i^b \leftarrow (d_i - g_i^{wind/solar})\Delta t + SoC^{change} \cdot \eta^d$
14:     **end if**
15: **end for**
16: ▷ Post-Processing
17: $SoC_i$: State of Charge at time $i$
18: $e_i^s$: Energy exported to grid at time $i$ with selling price of $\tau_i^s$
19: $e_i^b$: Energy imported from grid at time $i$ with buying price of $\tau_i^b$

The algorithm proceeds as follows:

1. **Initialization**: The state of charge (SoC) is initialized to its initial value (Line 1), and

the number of timesteps is determined from the generation data (Line 2).

2. **Excess Energy Scenario**: When generation exceeds demand ($g_i^{wind/solar} \geq d_i$, Line 4), the algorithm calculates the maximum power that can be used to charge the battery without exceeding its maximum charging power (Line 5) or capacity (Line 6). The SoC is updated accordingly (Line 7). Any remaining excess energy is then exported to the grid (Line 8).

3. **Energy Deficit Scenario**: When demand exceeds generation ($g_i^{wind/solar} < d_i$, Line 9), the algorithm calculates the maximum power that can be discharged from the battery without exceeding its maximum discharging power (Line 10) or capacity (Line 11). The SoC is updated accordingly (Line 12). Any remaining deficit is then met by importing energy from the grid (Line 16).

4. **Post-Processing**: The final state of charge, exported energy, and imported energy for each timestep are recorded for further analysis (Lines 17-19). Note that the exported energy ($e_i^s$) and imported energy ($e_i^b$) are not needed, as they can be calculated from the state of charge ($SoC_i$), generation ($g_i^{wind/solar}$), and demand ($d_i$).

### 4.1.2 Linear Programming (LP) Optimization Model

In contrast to the model-free greedy algorithm, the linear optimization model takes a more strategic approach to battery management by optimizing the charging schedule over an event (or look-ahead) horizon. For this thesis, the horizon was set to one day (24 hours), aligning with much of the current literature on battery optimization [50] as well as the operational practices at GIGA. Unlike the instantaneous decision-making of the greedy algorithm, which reacts to each timestep independently, the linear optimization model considers the entire day's energy dynamics and returns a schedule that minimizes the community's energy bill.

This approach requires that the input data be known beforehand, either through forecasting or the use of historical patterns. In this study, historical data was used for energy generation ($g_i^{wind/solar}$), energy demand ($d_i$), and energy tariffs ($\tau_i$), as described in Section 4.3. The event horizon denotes how far into the future the algorithm can access data. Increasing the event horizon usually results in a better overall schedule. However, this is not always practical, as predicting values further into the future often reduces the accuracy of the predictions. For this study, an event horizon of one day was chosen, as this was deemed achievable in practice.

Model 1 outlines the Linear Optimization model used for the community simulation. The objective function minimizes the energy bill, which consists of the cost of the imported energy and the penalties associated minus the revenue from the exported energy (Equation 1.0). Two regularisation costs ($L_1$ and $L_2$) are also added to improve the behaviour of the model.

The model's constraints ensure the battery's state of charge (SoC) is updated correctly at each timestep. The initial state of charge is set to its initial value (Equation 1.1). The SoC at each subsequent timestep is determined by the previous SoC, the charging power, and the discharging power, adjusted by their respective efficiencies (Equation 1.2). The power balance constraint ensures that the difference between charging and discharging power matches the net energy generation minus demand, adjusted for energy imports and exports (Equation 1.3). Additionally, the maximum daily depth of charge $\lambda^{max\_cycles}$ prevents excessive cycling, prolonging the life of the battery (Equation 1.4).

**Model 1** LP Model - Community Simulation

**Objective function:**

Minimize $\sum_{i=1}^{T}\left(\tau_i^b \cdot e_i^b - \tau_i^s \cdot e_i^s\right) + L_1 + L_2$ ▷ (1.0)

**Constraints:**

$SoC_0 = SoC_{initial}$ ▷ (1.1)

$SoC_{i+1} = SoC_i + \eta_c \cdot p_i^{charge} \cdot \Delta t - \frac{p_i^{discharge}}{\eta_d} \cdot \Delta t$ ▷ (1.2)

$p_i^{charge} - p_i^{discharge} = g_i^{wind/solar} - d_i + e_i^b - e_i^s$ ▷ (1.3)

$\sum_{i=1}^{T} \frac{(p_i^{charge} \cdot \eta_c + p_i^{discharge}/\eta_d) \cdot \Delta t}{2 \cdot (SoC^{max} - SoC^{min})} \leq \lambda^{max\_cycles}$ ▷ (1.4)

**Decision variables:**

$SoC_i \in [SoC^{min}, SoC^{max}]$ ▷ State of charge at time step $i$

$p_i^{charge} \in [0, p^{max}]$ ▷ Battery charging power at time step $i$

$p_i^{discharge} \in [0, p^{max}]$ ▷ Battery discharging power at time step $i$

$e_i^b \in [0, \infty]$ ▷ Energy import at time step $i$

$e_i^s \in [0, \infty]$ ▷ Energy export at time step $i$

**Regularization costs:**

$L_1 = \sum_{i=1}^{T}\left(\lambda^{charging} \cdot p_i^{charge} + \lambda^{charging} \cdot p_i^{discharge}\right)$ ▷ Penalty for using the battery

$L_2 = \lambda^{capacity} \cdot (Soc^{max} - SoC_T)$ ▷ Penalty for empty battery

The linear optimization model is more versatile than its greedy counterpart, particularly when energy prices fluctuate over time. In such scenarios, the linear optimizer can anticipate and decide the optimal times to utilize the grid. For example, it might be more advantageous to buy energy during the night when prices are lower and store it until needed for a deficit. Additionally, the linear model actively trades in the energy market, buying energy with the intent of selling it at a higher price later, rather than solely for deficit purposes. This capability allows the linear model to balance the community's needs while also optimizing economic benefits.

Finally, we will examine two regularization costs designed to improve the final schedule by guiding the linear model toward a better solution. In linear optimization, multiple solutions with the same objective function often exist, making them all optimal from the optimizer's perspective. The regularization costs are meant to refine these solutions, by slightly changing their ordering.

The L1 cost aims to reduce battery usage by adding a very small cost, $\lambda^{charging}$, every time the battery is charged or discharged. Incorporating this cost into the objective function makes the solution with the least battery usage slightly more favorable. This cost must be small to avoid affecting the overall optimality of the solution. In our study, we used a value of $\lambda^{charging} = 10^{-7}$.

Figure A.2 shows a comparison between the SoC resulting from the greedy and simple linear models over 10 days. As illustrated in Figure A.3, adding the L1 regularization cost results in an improved schedule, while the total simulation cost remains constant.

The L2 cost aims to keep the battery charged at the end of the day. A drawback of the one-day time horizon is that the linear model does not charge the battery at the end of the day because it lacks information about the next day's loads. Consequently, it always opts to export energy at day's end. The L2 optimization adds a small cost, $\lambda^{capacity}$, which penalizes the model for any unused capacity left in the battery at the end of the day. This incentivizes the model to charge the battery when possible. An undesired effect of this cost is that if the buying price falls below the $\lambda^{capacity}$ parameter, the model may purchase power to charge the battery unnecessarily. In this study, we used a value of $\lambda^{capacity} = 1.2$, chosen experimentally based on performance across all scenarios. The effects of L2 regularization are illustrated in A.4.

The best schedule is achieved by applying both regularizations together, as shown in A.5. This approach not only produces the best results in all but one scenario but also significantly decreases battery wear, thereby extending the battery's lifespan.

### 4.1.3 Mixed Integer Linear Programming (MILP) Optimization Model

As discussed in Section 3.3, the LP model requires additional constraints to accurately model mutually exclusive operations, such as charging and discharging or importing and exporting. Without these constraints, the model permits simultaneous operations, which can distort the objective function. It has been found that for the set-point tracking (SPT) problem, the LP formulation can overestimate the objective function by as much as 15%[50]. The SPT problem involves a central aggregator that controls multiple BESSs and is tasked with matching the net power demand (demand minus local renewable generation) within the system. The problem studied in this thesis can be considered a base case of the SPT problem, where the aggregator has access to only one BESS.

This issue was also encountered in this thesis and studied further. For the problem studied here, the LP model shown in Model 1 also overestimates the objective function. To address this, two binary variables were introduced, one for battery operation and the other for grid operation, to ensure that only one action can be performed in each case. The new model, shown in Model 2, is significantly slower due to the introduction of the binary variables, which turn the model into a mixed-integer linear programming (MILP) model. However, the MILP model reports the correct final cost.

From experimental evidence, we believe that the LP model miscalculates the objective function due to the difference between charging and discharging efficiencies. When both the charging power and discharging power are set above zero, the model creates excess power. For example, if the charging and discharging capacities are set above zero, we will not import anything from the grid because the two values cancel out in Equation 1.3. However, in Equation 1.2, the two terms do not cancel out completely due to the asymmetric charging

($\eta^c$) and discharging efficiency ($\eta^d$) terms. This results in extra energy that we do not have to pay for, leading to a lower objective function.

Importing and exporting at the same time can alter the objective function even more than the issue previously discussed. However, we found this not to be a problem in practice. When the buying price of energy is higher than the selling price, which is most often the case, the model naturally avoids performing both actions simultaneously, as it would result in a financial loss. However, if the selling price exceeds the buying price, the model can import and export an infinite amount of energy simultaneously, creating unlimited profit potential. This is not only unrealistic but also results in an unbounded model, as there is no upper limit on the import and export variables, and increasing them always improves the objective function. To avoid this situation, which would result in an unsolvable model, in all the studied scenarios, the buying price of electricity was always smaller than or equal to the selling price of electricity.

However, we have found a way to obtain the real cost using the schedule given by the LP formulation. The final cost can be recomputed using only the state of charge (SoC) and the inputs of the problem (demand, generation, and energy prices). First, we can recompute the charging and discharging power from Equation 1.2 solely from the SoC. Solving for two unknowns using only one equation results in an infinite number of solutions. This is the same problem that the LP faces, as all these solutions are valid in the solution space of the relaxed problem. However, we know that only one of the two variables can be positive, with the other set to zero. So, depending on the sign given by the difference of the SoCs at consecutive time steps, we know whether we are in the charging or discharging case. This allows us to calculate the correct charging power at any given time step. Note that by doing so, we are never outside the problem constraints. Even if the LP solution allows both charging and discharging at the same time step, using both variables at the same time can never exceed the maximum power and will only result in a smaller net power than if one variable remains at its value and the other is set to zero. From here, we can just plug everything into Equation 1.3. Similarly, we can assume that we only import or export at any given time, so depending on the sign of the equation, we set either one or the other. Finally, we can recompute the final cost as seen in Equation 1.0. This cost matches the one reported by the MILP model, despite being calculated from the SoC reported by the LP model, which had an incorrect objective function.

The procedure described above, although straightforward, has not been encountered in the relevant literature. It provides a valid way of mapping a solution generated by the relaxed LP model to the solution space of the MILP model and obtaining the correct final cost. For the rest of this thesis, this procedure will always be used to calculate the final cost. The need for this procedure also arises from the fact that the regularization costs skew the objective function of the models. Although not the main focus of this thesis, the comparison between the MILP model, LP model, and the procedure described above is an interesting topic for future research.

**Model 2** MILP Model - Community Simulation

**Objective function:**

Minimize $\sum_{i=1}^{T}\left(\tau_i^b \cdot e_i^b - \tau_i^s \cdot e_i^s\right) + L_1 + L_2$ ▷ (2.0)

**Constraints:**

$SoC_0 = SoC_{initial}$ ▷ (2.1)

$SoC_{i+1} = SoC_i + \eta_c \cdot p_i^{charge} \cdot \Delta t - \frac{p_i^{discharge}}{\eta_d} \cdot \Delta t$ ▷ (2.2)

$p_i^{charge} - p_i^{discharge} = g_i^{wind/solar} - d_i + e_i^b - e_i^s$ ▷ (2.3)

$\sum_{i=1}^{T} \frac{(p_i^{charge} \cdot \eta_c + p_i^{discharge}/\eta_d) \cdot \Delta t}{2 \cdot (SoC^{max} - SoC^{min})} \leq \lambda^{max\_cycles}$ ▷ (2.4)

$p_i^{charge} \leq p^{max} \cdot (1 - x_i)$ ▷ (2.5)

$p_i^{discharge} \leq p^{max} \cdot x_i$ ▷ (2.6)

$e_i^b \leq 10^{15} \cdot (1 - y_i)$ ▷ (2.7)

$e_i^s \leq 10^{15} \cdot y_i$ ▷ (2.8)

**Decision variables:**

$SoC_i \in [SoC^{min}, SoC^{max}]$ ▷ State of charge at time step $i$

$p_i^{charge} \in [0, p^{max}]$ ▷ Battery charging power at time step $i$

$p_i^{discharge} \in [0, p^{max}]$ ▷ Battery discharging power at time step $i$

$e_i^b \in [0, \infty]$ ▷ Energy import at time step $i$

$e_i^s \in [0, \infty]$ ▷ Energy export at time step $i$

$x_i \in \{0, 1\}$ ▷ Binary variable indicating if the battery is discharging at time step $i$

$y_i \in \{0, 1\}$ ▷ Binary variable indicating if the grid is exporting energy at time step $i$

**Regularization costs:**

$L_1 = \sum_{i=1}^{T}\left(\lambda^{charging} \cdot p_i^{charge} + \lambda^{charging} \cdot p_i^{discharge}\right)$ ▷ Penalty for using the battery

$L_2 = \lambda^{capacity} \cdot (Soc^{max} - SoC_T)$ ▷ Penalty for empty battery

### 4.1.4 Self-Consumption and Degree of Autarky

In recent years, the "Clean Energy for All Europeans" package introduced the concept of self-consumption (SC) for energy communities [24, 34]. Self-consumption measures how much of the energy produced is consumed within the Renewable Energy Community (REC). Increasing SC within RECs can reduce strain on the grid, which is crucial given the increasing network congestion issues on the transmission and distribution grids in the Netherlands and the EU. Therefore, many people in RECs are motivated not only by the financial benefits of renting a BESS but also by the prospect of increasing their SC. Some individual prosumers and energy communities may even prioritize higher SC over achieving the lowest possible energy bill. To better understand the problem, we will also examine how varying BESS capacities affect the community's SC.

The Self-Consumption (SC) coefficient[31] is defined as the ratio between the energy used from self-production and the total produced energy, as shown in Equation 4.1. One drawback of this metric is that it decreases when the community exports more energy, penalizing the installation of excess capacity and encouraging smaller installations. This reflects a valid concern that exporting too much energy can negatively impact grid stability. However, this metric may overly encourage small-scale generation, leading to a very high SC coefficient even when local production does not meet most of the community's demand, which is unrealistic.

$$SC = \frac{\sum_i^T g_i^{wind/solar} - \sum_i^T e_i^s}{\sum_i^T g_i^{wind/solar}} \tag{4.1}$$

Another metric used in this study is the Degree of Autarky (DoA)[31], which measures the percentage of energy consumption met by locally produced sources. The DoA is defined as the ratio between the locally satisfied consumption and the total consumption, as shown in Equation 4.2. Although SC and DoA are similar, the key difference is that DoA does not decrease with excess production exported to the grid. DoA promotes balancing supply and demand within the community and increases with higher generation or battery capacities, making it a more stable metric for measuring the community's self-reliance.

$$DoA = \frac{\sum_i^T d_i - \sum_i^T e_i^b}{\sum_i^T d_i} \tag{4.2}$$

## 4.2 Energy Spot Market Simulation

The spot market simulation will also employ a linear model as described in Model 3. This model operates on a daily time horizon, similar to its community counterpart, and is executed independently for each day of the year. However, Model 3 is simpler than Model 1, as it does not account for demand and generation. The battery is always charged using imported energy, and discharged energy is always exported. Another notable difference is in the objective function, in this case, the profits are maximized. Formulating the problem as profit maximization or cost minimization results in equivalent linear programming formulations, the only difference being the sign of the objective function.

The only input for the model is the electricity prices at each time step. The prices from either the day-ahead market or the imbalance market can be used, with the main difference being the time step duration (hourly vs. quarter-hourly). The model output will be the optimal schedule, i.e., the schedule that maximizes profits. The constraints ensure the proper functioning of the model: the state of charge (SoC) starts at an initial value and updates based on the charging and discharging powers at each timestep. The imported energy equals the charging power times the length of the time step. An identical constraint is also added for the exported energy. Additionally, the model ensures that the depth of charge does not exceed a maximum daily cycle limit. The decision variables include the state of charge at each time step, the battery charging and discharging power, and the energy imported and exported at each time step.

**Model 3** LP Model - Market Simulation

**Objective function:**

Maximize $\sum_{i=1}^{T}\left(\tau_i^s \cdot e_i^s - \tau_i^b \cdot e_i^b\right)$ ▷ (3.0)

**Constraints:**

$SoC_0 = SoC_{initial}$ ▷ (3.1)

$SoC_{i+1} = SoC_i + \eta_{cd} \cdot p_i^{charge} \cdot \Delta t - p_i^{discharge} \cdot \Delta t$ ▷ (3.2)

$e_i^b = p_i^{charge} \cdot \Delta t$ ▷ (2.3)

$e_i^s = p_i^{discharge} \cdot \Delta t$ ▷ (3.4)

$\sum_{i=1}^{T} \frac{(p_i^{charge} \cdot \eta_{cd} + p_i^{discharge}) \cdot \Delta t}{2 \cdot (SoC^{max} - SoC^{min})} \leq \lambda^{max\_cycles}$ ▷ (3.3)

**Decision variables:**

$SoC_i \in [SoC^{min}, SoC^{max}]$ ▷ State of charge at time step $i$

$p_i^{charge} \in [0, p^{max}]$ ▷ Battery charging power at time step $i$

$p_i^{discharge} \in [0, p^{max}]$ ▷ Battery discharging power at time step $i$

$e_i^b \in [0, \infty]$ ▷ Energy import at time step $i$

$e_i^s \in [0, \infty]$ ▷ Energy export at time step $i$

## 4.3 Data Gathering and Preprocessing

This section outlines the methodology used to collect the input data required for the algorithms described above. For the community simulation, both demand and generation curves were needed along with energy prices. For the company simulation, energy prices for the Day-Ahead and Imbalance Markets were required.

### 4.3.1 Community Demand

In this thesis, real demand data was sourced from The Thames Valley Vision (TVV) [5] dataset. The dataset includes both generation and demand curves for 200 class-1 and 20 class-2 from the UK[4]. However, the generation data is comparatively small and will be ignored in this study, focusing solely on the demand data. Specifically, this study uses the 200 class-1 households, representing unrestricted domestic consumers [42]. The total yearly demand for this community is approximately 840.34 MWh. The average yearly demand per household is around 4201.71 kWh, with the smallest household consuming 1000 kWh annually and the largest household consuming 18735.47 kWh. Figure 4.1 presents a histogram of the yearly demands (in kWh) for the households in the dataset.

### 4.3.2 Community Wind Generation

The wind generation curve can be estimated from wind speeds using a methodology similar to Fruh [21, 22], Andoni et al. [10], and Norbu et al.

Real wind speed data collected by the Royal Netherlands Meteorological Institute (KNMI) was used for the calculation. KNMI provides climate data averaged over several decades for 46 weather stations, as well as the provincial averages of the 12 Dutch provinces. For this

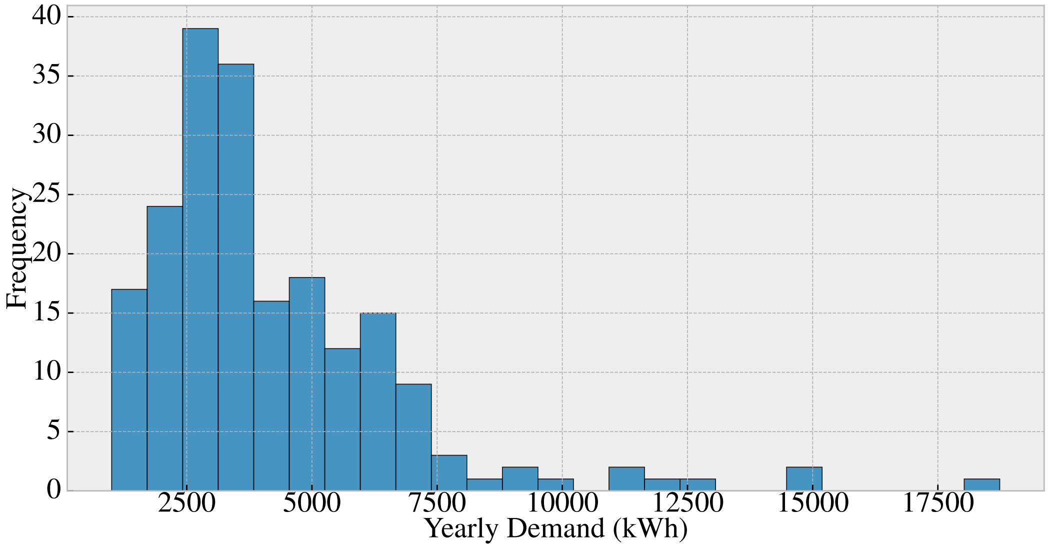



Figure 4.1: Histogram of yearly demands for the Thames Valley Vision Project. (€ per KWh).

study, data from North Holland was used, as this is where all of GIGA's assets are located, and the community should be situated around these assets.

The data was retrieved from TU Delft's Meteorological data portal[1], and it consists of average wind speeds for a year with hourly time steps, measured at a height of 10m above the ground. Any missing data is computed using double spline interpolation function. The hitorical and interpolated wind speed can be see in Figure 4.2.

$$u_h = u_a \frac{log z_h / z_0}{log z_a / z_0}$$

where $u_h$ is the wind speed at the wind turbine hub height $z_h = 50m$, $u_a$ is the wind speed measured at the anemometer height $z_a = 10m$, and $z_0 = 0.03m$ is the surface roughness of grass, which is a typical environment around weather stations and was also used by [21, 22, 10, 42].

The final power output can be approximated using the power curve provided by the manufacturer, as seen in Figure 4.3. For this study, we will use the power curve of the Energon E-33 wind turbine [49], which can be approximated by a sigmoid function with parameters $a = 0.7526 s/m$ and $b = 8.424 m/s$:

$$f(x,a,b) = \frac{1}{1+e^{-a(x-b)}} \tag{4.3}$$

The yearly cost of the wind turbine was calculated and added to the community's final bill. Without including this cost, energy generation would appear free, making a larger

[1] https://www.tudelft.nl/en/ewi/over-de-faculteit/afdelingen/electrical-sustainable-energy/photovoltaic-materials-and-devices/dutch-pv-portal/meteorological-data

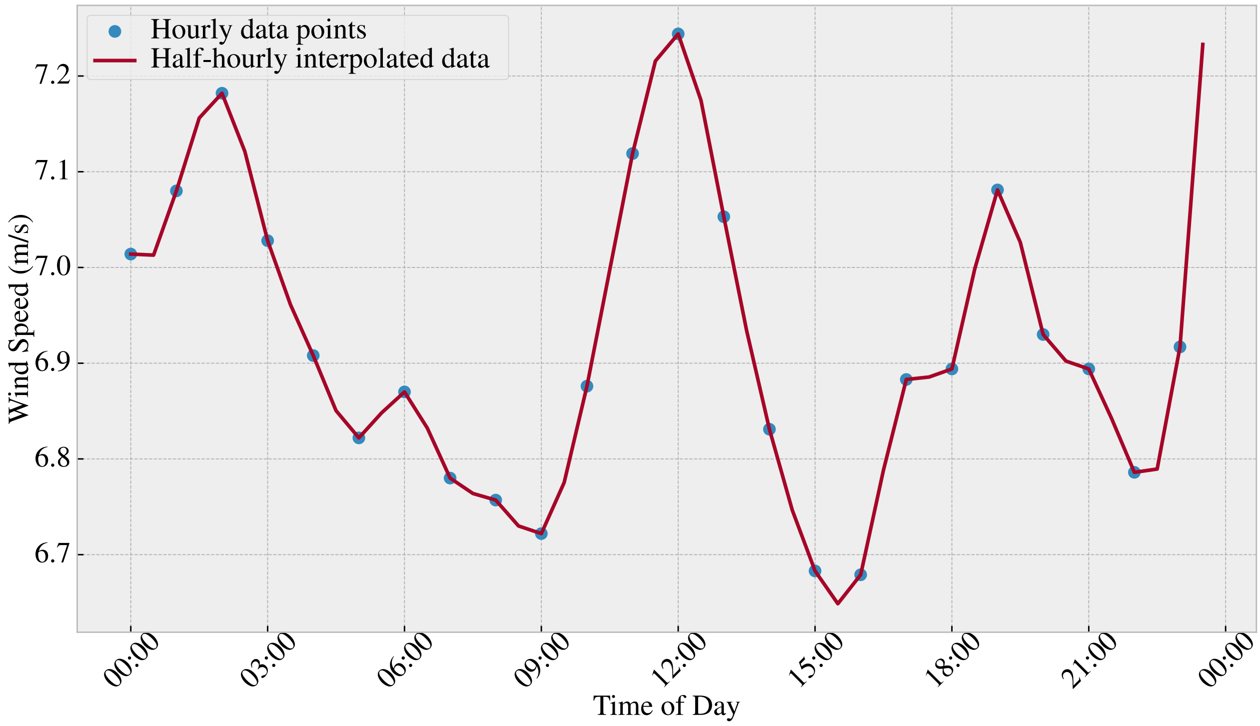



Figure 4.2: Historical wind speed data from North Holland as recorded by KNMI with interpolated values for missing timesteps.

turbine always advantageous, which is unrealistic. Incorporating this cost allows for optimizing the scale of generation by considering the turbine's expense. The installation cost for wind turbines has steadily declined in recent years. For our study, we used the average weighted price from 2022 of €1200 per kW of installed capacity [1]. The wind turbine's cost is amortized over 20 years, resulting in a yearly cost of €19,800. One cost not considered in this thesis is the maintenance cost of the wind turbine. This cost is more challenging to compute as it depends on multiple factors, such as the age and capacity of the turbine and the type of technology used. Therefore, this cost was not included, but readers should be aware of these costs, usually referred to as operations and maintenance (O&M) costs [20].

Finally, we need to ensure that the sizes of local renewable generation capacity and demand are aligned at realistic levels relative to each other. This is achieved through a scaling coefficient. The scaling coefficient for the community tracks how much of the yearly demand is produced by the wind turbine in a year. The scale of the original wind turbine is approximately 1.2. This coefficient helps us answer RQ1(c) by varying the scale of the generation and selecting the one that lowers the total bill. Note that for all other research questions, the original scale was used. The net generation, which is the produced energy minus the demand, for the whole year can be seen in Figure A.1. In this figure, the community does not have access to a battery, so the surplus or deficit is always exported or imported. Because the scale is close to 1, the community imports approximately the same amount it

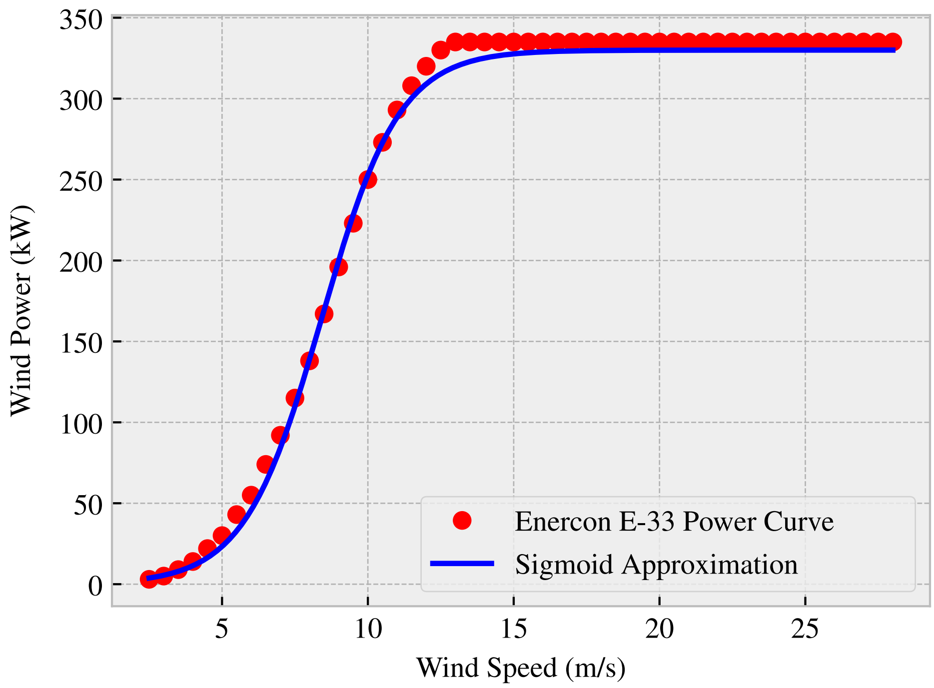



Figure 4.3: Comparison between the power curve of the Enercon E-33 wind turbine [49] and the sigmoid approximation described by Eq. 4.3.

exports. The same net generation for a scale of 0.75 can be seen in Figure A.1. Increasing or decreasing the scale will shift the line up or down. Including a battery will reduce both the exported and imported energy, as some of the exported energy will be stored and become available for later use.

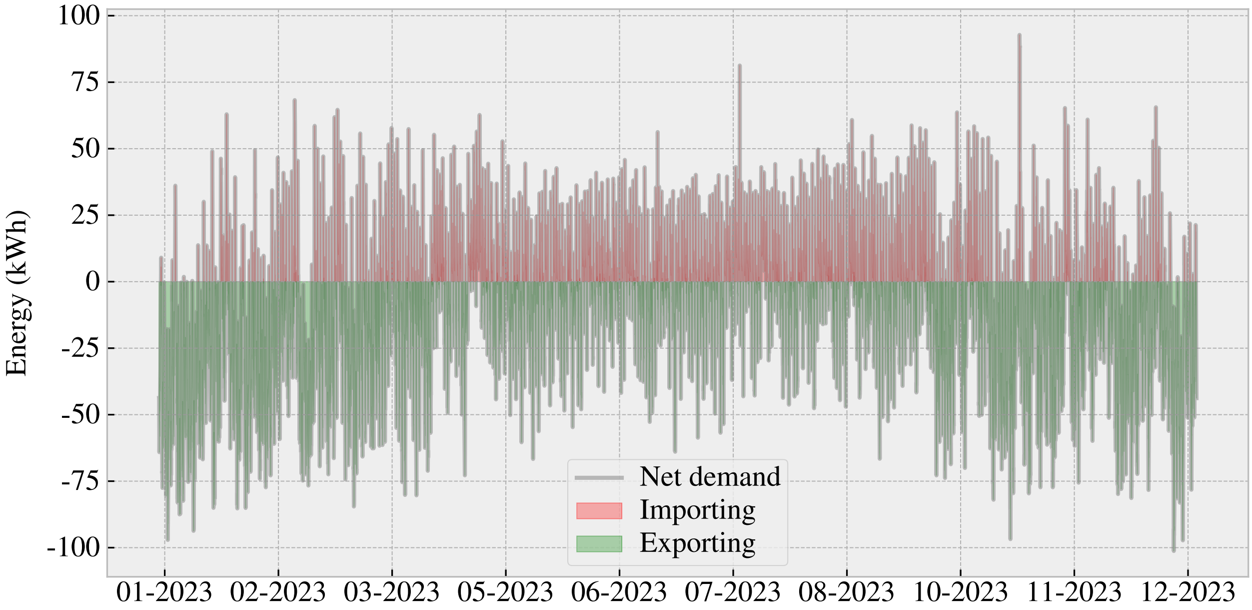



Figure 4.4: The half-hourly net generation ($g_i - d_i$) for a community of 200 households, using a 330kW Energon E-33 wind turbine [49].

### 4.3.3 Energy Prices

This thesis examines three types of energy tariffs: fixed prices, dynamic prices, and market prices. While fixed and dynamic tariffs are typically available to prosumers in the Netherlands, market prices are generally accessible only to BRPs such as GIGA. However, this study includes scenarios where community participants can also access market prices. We will discuss the structure, benefits, and drawbacks of each tariff type.

#### Fixed energy tariffs

The fixed energy tariffs, also known as flat-rate pricing, remain constant over a billing period, regardless of the time of day or demand conditions. (There exists another variation called tiered pricing, where consumers pay different rates based on their total consumption, with higher rates for higher usage). The flat-rate pricing is simple and predictable, making it easier for a consumer to understand and budget their energy costs accordingly. However, this type of tariff does not encourage the consumer to shift their usage away from on-peak hours, leading to a higher-peak demand. Furthermore, consumers using this type of pricing usually pay higher overall costs, as the flat rate includes a risk premium added by the energy supplier.

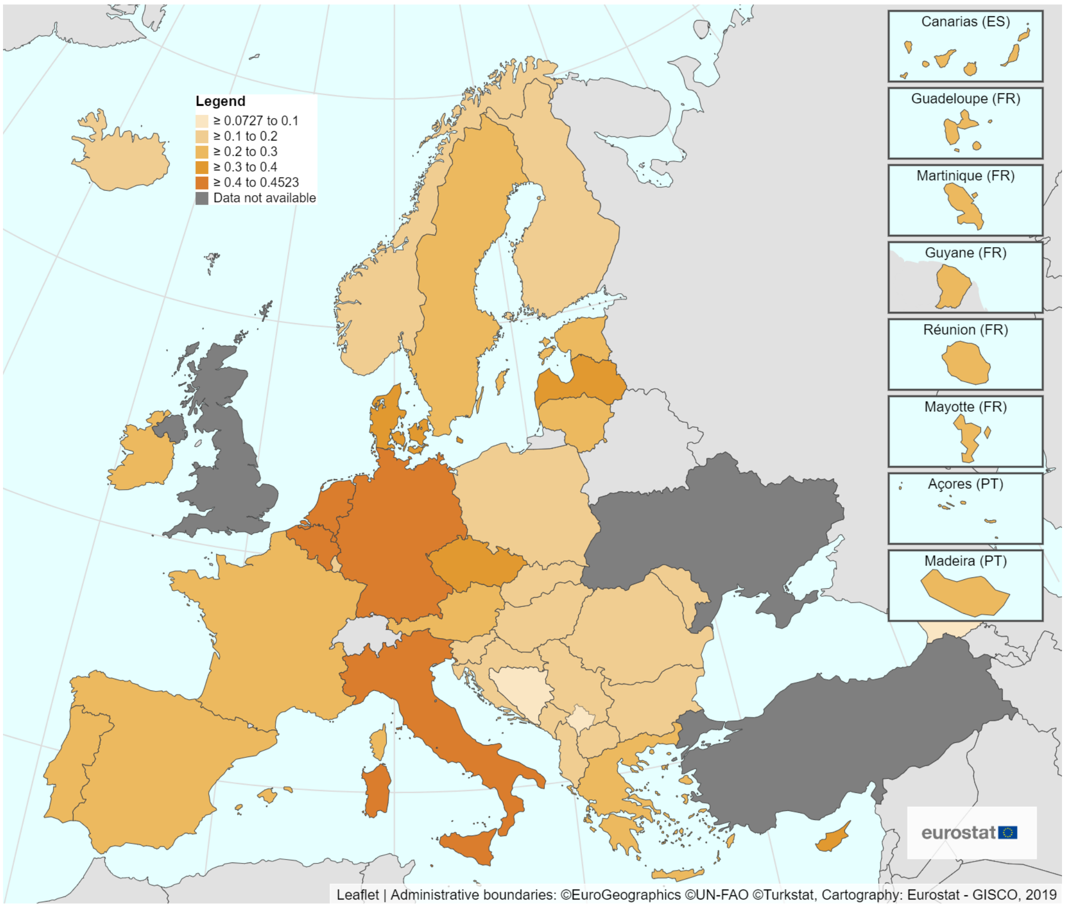



Figure 4.5: Map of average electricity prices (€ per kWh) for household consumers in Europe (first half of 2023), created using Eurostat[2].

The flat tariffs vary depending on multiple factors, such as region, energy supplier, and the type of consumer (industrial or residential). Eurostat [2] reports that during the first half of 2023, the energy prices in the Netherlands (both with and without taxes and levies) were the highest in Europe, averaging at 0.4523 € per kWh. In comparison, the European Union had an average energy price of 0.2965 € per kWh. You can see an overview of all the European countries in Figure 4.5.

Table 4.1 shows the price breakdown by consumption bands in the Netherlands for 2023. The table indicates that the households that paid the most in the Netherlands in 2023 were the ones with consumption of less than 2.500 kWh in a year. However, in 2023, the Dutch government has set a cap of 0.40 €/kWh for the electricity price, for all consumers under 2,900kWh. Without this government subsidy, most households and small-scale users would have a higher energy bill[26]. As for the output price, the energy providers usually offer a price between zero and twenty cents [44].

As we can see, it is hard to pinpoint an exact price of electricity, as it depends on multiple factors. In our study, we consider a range of flat tariffs from €0.10 to €0.40 per kWh for imported energy, along with scenarios where communities either do not receive compensation for exported energy or receive a fixed tariff of €0.10 per kWh.

Table 4.1: The buying price of energy for in the Netherlands (in € per kWh) and the ranking of that price when compared with all countries in the European Union (bigger is better), for the two halves of the year 2023, taken from Eurostat [2].

| Yearly Consumption | First Half of 2023 | Second Half of 2023 |
|---|---|---|
| | Price (Ranking) | Price (Ranking) |
| less than 1000 kWh | 0.7928 (1) | 0.6072 (1) |
| from 1000 to 2499 kWh | 0.5176 (2) | 0.3436 (3) |
| from 2500 to 4999 kWh | 0.4436 (2) | 0.2659 (7) |
| from 5000 to 14999 kWh | 0.3869 (2) | 0.2046 (12) |
| over 15000 kWh | 0.4184 (1) | 0.2177 (8) |
| All Bands | 0.4551 (1) | 0.2819 (5) |

### Dynamic energy tariffs

Dynamic energy tariffs, also known as time-of-use (TOU) tariffs, are higher during peak demand periods and lower during off-peak hours. This pricing model encourages consumers to use electricity during off-peak times, helping to balance demand and potentially lowering overall energy costs for those who can adjust their usage. It reduces strain on the grid and enhances grid stability and efficiency. However, the unpredictability of dynamic pricing can make it challenging for consumers to budget their energy costs, as it requires consumers to actively monitor and respond to price signals.

For instance, Frank Energie [2] offers dynamic tariffs in the Netherlands that reflect market conditions. These tariffs are subject to additional taxes, such as VAT (known as BTW in Dutch), energy tax, and variable fees, which typically range from €0.13 to €0.18 per kWh, depending on various factors like the time of day and market prices. A flat tariff of €0.155 per kWh will be used instead, as the historical tariffs are unavailable. This flat rate will be added on top of the day-ahead market price. For the export tariff, a flat rate of €0.10 per kWh will be applied, which is realistic based on information from Frank Energie's website. Additionally, a scenario where no money is received for exported energy will also be considered.

### Market Prices

The historical prices from both the day-ahead and the imbalance market are needed for the company simulation. Additionally, the day-ahead prices are used to calculate the dynamic import price for consumers. The prices for both markets in the Netherlands for 2023 were retrieved from the ENTSO-E (European Network of Transmission System Operators for Electricity) API, using an open-source library [3].

[2] `https://www.frankenergie.nl/`

[3] `https://github.com/EnergieID/entsoe-py`

Typically, a transport tariff is applied on top of market prices. This transport tariffs are supported by the buyer. However, as mentioned in Section 2.3,GIGA can import locally produced renewable energy at the market price without paying transport costs. Therefore, for the company's simulation, we will use the market prices without transport cost. This makes the company's current stacked revenue model more profitable and harder to find an equally or better opportunity.

As previously mentioned, normal prosumers do not have access to this type of tariff. However, in this situation, their battery is owned by GIGA, which is a BRP, allowing access to these prices and enabling them to offer the same to the community. This creates an interesting case study. For the community simulation, we will use two types of market prices: with and without transport taxes. In the case of transport taxes, a flat transport tariff of €0.2 per kWh was added to the buying price of electricity.

# Chapter 5

# Experimental Results

This chapter presents the experiments conducted to address the research questions outlined earlier, while also discussing the corresponding results. The first two subsections are dedicated to answering RQ1, while the final subsection focuses on answering RQ2.

## 5.1 Calculating the Battery Rental Price

This section will analyze the experiments used to determine the rental price of the battery, with the intent of answering RQ1(a). From the community's perspective, there is a maximum price they are willing to pay, which corresponds to their potential savings for a given battery capacity. From the company's perspective, there is a minimum price they are willing to accept, which corresponds to the profit they would have earned with the same battery size in the energy markets. Renting out the battery is viable only when these two bounds are in the correct order. We will now discuss the results from each of these perspectives.

### 5.1.1 The Maximum Rental Price

In order to better understand the problem, we will first look at the community's yearly costs for multiple battery sizes. The community costs are comprised of the energy bill and the amortized cost of the wind turbine, with the cost of the battery being excluded for the moment. The yearly costs for different battery sizes and flat tariffs can be seen in Figure 5.1, with each line representing a different flat tariff scenario. All combinations between four different buying prices $\tau^b \in \{0.4, 0.3, 0.2, 0.1\}$ and two selling prices $\tau^s \in \{0.0, 0.1\}$ (in € per kWh) were explored. For all except the last scenario, the cost goes down as the battery increases.

The scenarios form two distinct groups. The upper four lines correspond to the case in which the community does not get paid for their exported energy (the export tariff is set to zero $\tau^s = 0$). In this case, all the lines approach the yearly wind turbine cost of around €20000. This is expected, as the community energy bill will go toward zero as the battery capacity increases, leaving just the wind turbine cost in the final bill.

The lower four lines correspond to the case in which the community gets paid for the exported energy (the export tariff is set to ten cents, $\tau^s = 0.1$). In this scenario, the costs

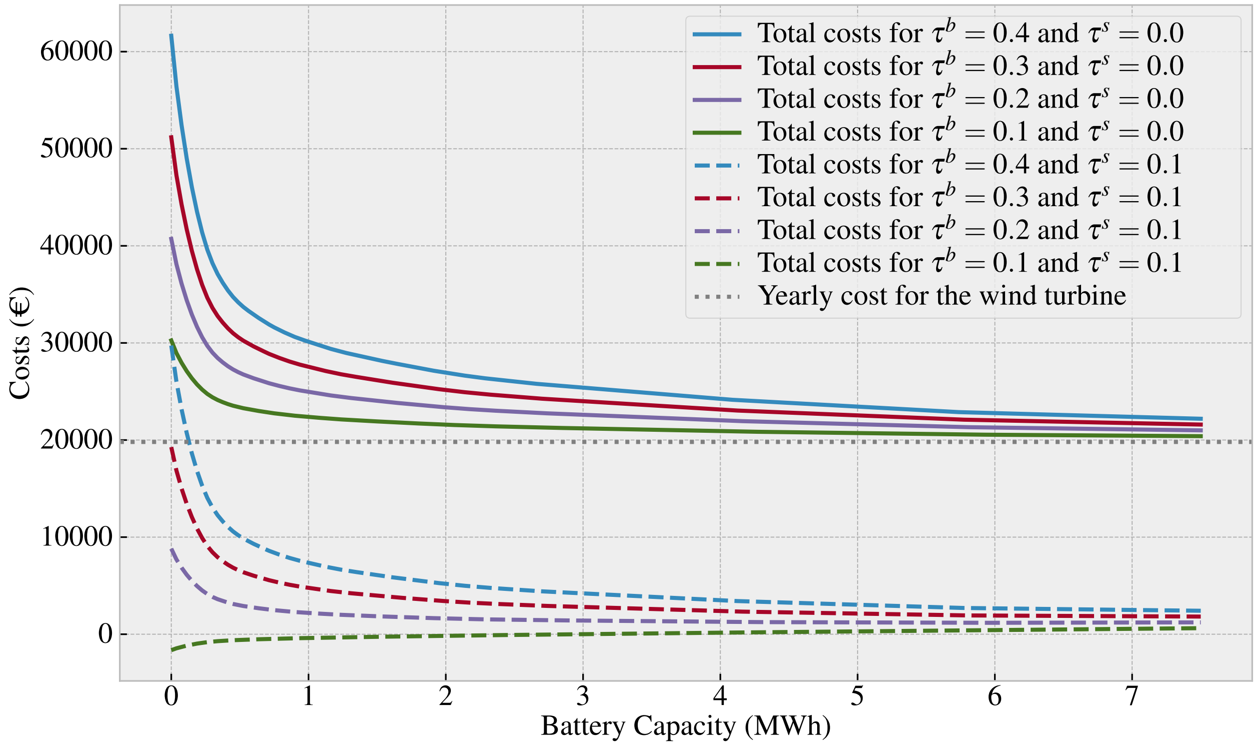



Figure 5.1: The yearly costs for the community (excluding the battery) for different battery capacities and flat tariff scenarios.

approach zero, meaning that the profit sold to the grid is approximately the same as the cost of the wind turbine. This is an interesting finding, as it indicates that the wind turbine could pay for itself if the community is allowed to export the excess generation. Consequently, the only costs the community would have to pay are the rental price of the battery and the operation and maintenance (O&M) costs of the wind turbine, which were not discussed in this thesis.

A widely accepted metric is the monetary (or financial) savings for the community. The savings directly correspond to how much the community is willing to pay for the battery, i.e., the maximum rental price. They can be directly computed from the costs by calculating how much the community lowers their bill when compared to the case with no battery. The savings for the community, for different battery capacities and flat tariff scenarios, can be seen in Figure 5.2.

An important observation is that the export cost does not significantly influence the final savings. By looking at Figure 5.2, we can observe that adding a selling price of ten cents per kWh has approximately the same effect as subtracting ten cents from the buying price. The difference between the solid and dotted lines can be explained by the fact that the turbine generates roughly 1.2 times the yearly needs of the community, which means that we are slightly overproducing, allowing us to recoup more of our costs. As the scale of the generation approaches the yearly demand (i.e., a scale of 1), the gap between the two

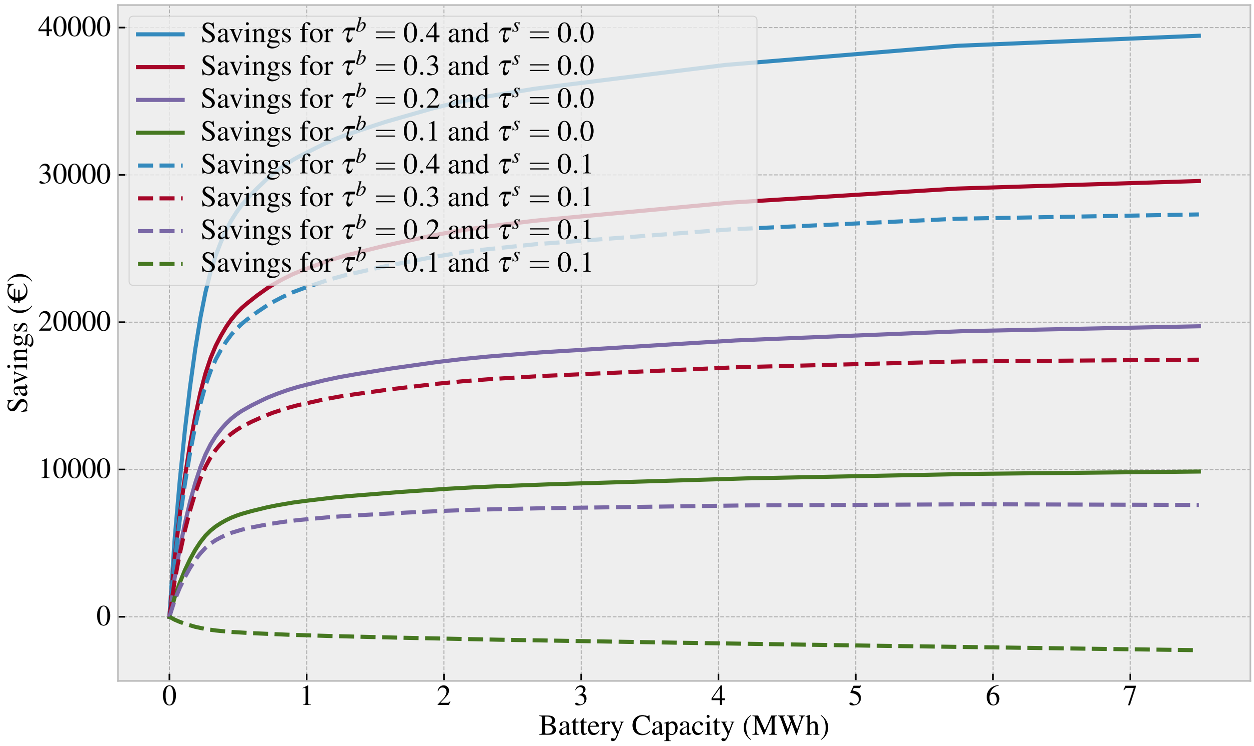



Figure 5.2: The yearly savings for the community (excluding the battery) for different battery capacities and flat tariff scenarios.

different types of lines would decrease.

We can also examine the Self-Consumption (SC) and Degree of Autarky (DoA) metrics, as shown in Figure A.7. Initially, the community has a relatively high degree of self-consumption, around 70%, even without a battery. This indicates that 70% of the energy produced by the wind turbine is directly consumed by the community. The DoA starts even higher, at 87%, meaning that 87% of the community's energy consumption is met by local sources. Another way to interpret these results is that without a battery, the community needs to export 30% of their produced energy and import an additional 13% to match demand when there is no generation, as shown in Figure A.7. Adding a battery helps store the overproduction of energy to be used at a later time, improving both metrics. Figure A.1 shows that adding a 1MWh battery increases the SC and DoA to 78.5% and 97%, respectively. Beyond this point, additional capacity results in minimal increases for both metrics. This aligns with existing literature, which suggests that achieving the final few percentages of DoA requires significant battery investments, with most of the capacity being rarely used [31]. For SC, the metric converges at a little over 80%, as seen in the results. This capping occurs because the SC metric penalizes the export of energy, which is the case here since the wind turbines are generating 1.2 times the yearly demand.

### 5.1.2 The Minimum Rental Price

This subsection will examine how the minimum rental price was determined. First, we will analyze GIGA Storage's earnings in the energy market and how this can be used to set a minimum price that makes financial sense. Finally, we will compare this rental price to the cost of buying a new BESS for the community.

The maximum and expected revenue on the Imbalance and Day-Ahead markets can be seen in Figure A.6a. The maximum revenues are based on the linear model described in Section 4.2 and the historical prices from the Netherlands in 2023. The values provided by the linear model represent the optimal yearly profits, which are not achievable in practice. In reality, we do not have access to all the information beforehand, requiring some forecasting that will lower the expected revenue. This is particularly noticeable for the Imbalance Market.

Figure A.6a shows that the Imbalance Market is much more profitable than the Day-Ahead Market. However, it is much harder to predict, making these potential profits much harder to achieve. The Day-Ahead Market is more predictable, so the achieved profits are closer to the maximum ones. Even with this consideration, our analysis has found that the Imbalance Market is too profitable to be replaced with a battery-as-a-service market model. However, the Day-Ahead Market has proven to be less profitable than the battery-as-a-service market model in some scenarios. For the rest of this thesis, we will focus on this scenario, considering only the Day-Ahead Market for the company simulation.

The minimum rental price directly corresponds to the profit that could have been achieved if the rented capacity had been used for price arbitrage on the wholesale markets instead of renting it to the community. This potential profit for the rented battery capacity can be directly computed from the potential revenue discussed previously and can be seen in Figure A.6b. This value represents the minimum rental price because setting it any lower would not make financial sense for the company, as they could generate more profit by performing price arbitrage on the energy markets. Note that Figures A.6a and A.6b are mirrored (y-axis) versions of each other.

We can empirically check if the minimum renting price would be a sensible choice by directly comparing it to the price of Li-ion batteries. In order to convert the minimum rental price, which is in €, we will have to divide the results in Figure A.6b by the rented battery size. This will convert the price to € per kWh, a common metric used to study the prices of batteries. This will allow us to directly compare the renting price with the cost of buying a new battery. The results can be seen in Figure 5.3. We can see that the rental price calculated from the Day-Ahead market remains flat across battery capacities, at around 35 € per kWh. This is not the case for the rental price based on the Imbalance Market, which starts very high, at around 270 € per kWh, and keeps increasing with additional capacity. The price of Li-ion batteries, which was considered to be between 160 and 130 € per kWh [43], can also be seen in light purple. Comparing these, we can see that renting out the battery at the price dictated by the Day-Ahead market would be cheaper for the community than buying a new battery themselves. On the other hand, for the Imbalance Market, it is clear that this revenue stream is too profitable to be replaced by the proposed BaaS model. However, we also need to consider that usually the prices of batteries are amortized over their lifespan,

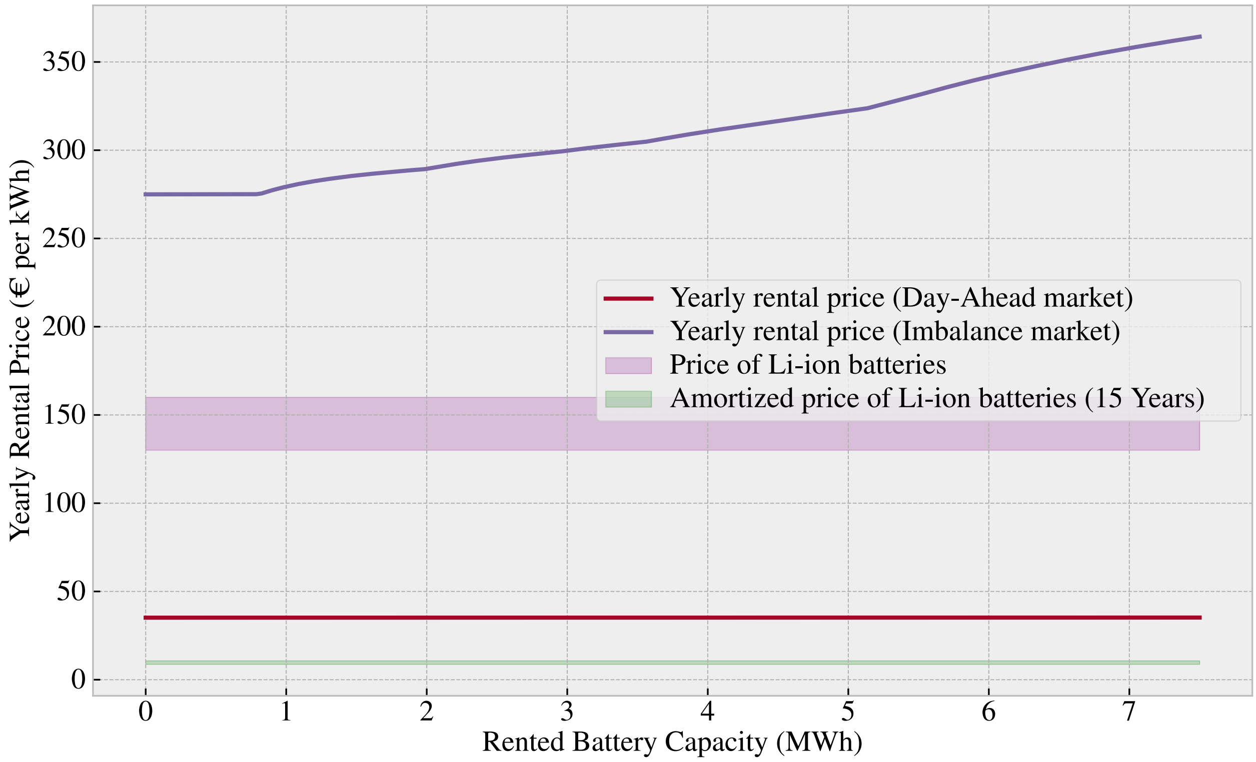



Figure 5.3: Comparison between the yearly rental cost and buying cost for the battery across different capacities.

which is usually 15 years. That would give us a yearly cost for the battery, resulting in an amortized yearly cost of between 8.5 and 10.5 € per kWh, which can be seen in light green. This would mean that buying the battery would be three times cheaper in the long run. However, as we will see in the next section, renting out the battery still makes financial sense for some capacities. We believe that BaaS can still be an attractive solution, especially for communities that are turned away by the high initial cost needed for purchasing BESSs.

### 5.1.3 Determining the Profitability Cut-Off Points for Battery Rental Prices

To better understand the profitability cut-off points for battery rental prices, both the minimum and maximum prices are shown in Figure 5.4. Multiple maximum prices exist depending on the flat-tariff scenario used. The area where the maximum price is greater than the minimum price is depicted in green. Selecting any combination of battery size and yearly rental price from the green area will result in both a lower bill for the community and an increase in profit for the company. The results show that renting out the battery can be profitable for both parties up to a capacity of 0.9 MWh if a flat import tariff of forty cents ($\tau = 0.4$) is used and no export is allowed ($\tau = 0$). The results indicate that the proposed methodology would be feasible in most of the studied scenarios.

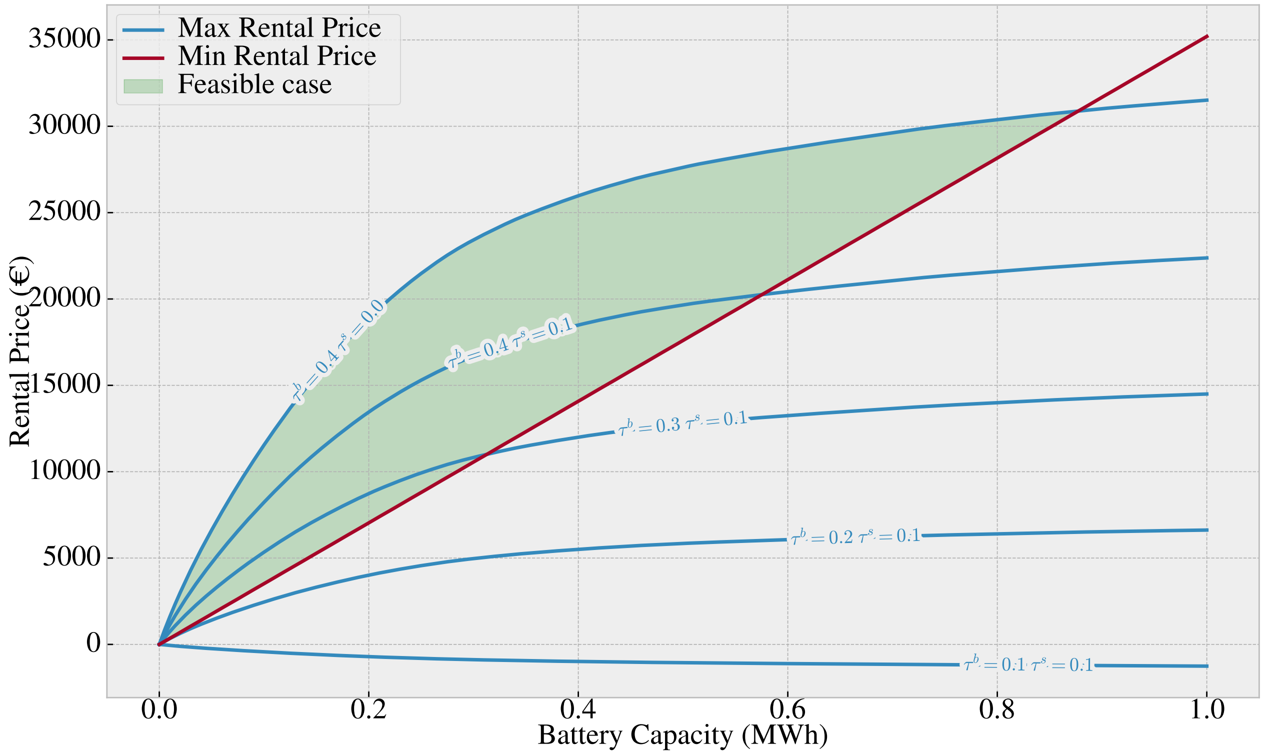



Figure 5.4: The minimum and maximum rental prices for different battery capacities and flat tariff scenarios.

## 5.2 Optimal Co-Sizing of Battery and Wind Generation Capacity

The experiments in this section are aimed at answering the remaining three subquestions from RQ1. First, we will optimize the battery with respect to the total cost and show that the battery is advantageous for most of the studied scenarios. We will then demonstrate how this methodology can be extended to analyze the optimal size for wind generation. Lastly, we will examine how self-consumption and the degree of autarky can be used to size the generation while also taking grid congestion into account. Throughout this section, the cost of the battery is included in the community's bill, with the rental price set at the minimum level that is still profitable for the company.

### 5.2.1 Optimal Battery Capacity for Maximizing Savings

In order to answer RQ1(b), the optimal battery size was calculated for each scenario and is shown in Figure 5.5. The optimal points for each scenario are indicated by dots. These points represent the optimal battery capacity that corresponds to the lowest achievable bill

Table 5.1: The minimum costs, maximum savings, battery capacity, self-consumption, and degree of autarky achieved at the optimum for each of the analyzed flat tariff scenarios.

| Import Tariff | $\tau^b = 0.4$ | | $\tau^b = 0.3$ | | $\tau^b = 0.2$ | | $\tau^b = 0.1$ | |
|---|---|---|---|---|---|---|---|---|
| Export Tariff | $\tau^s = 0.0$ | $\tau^s = 0.1$ | $\tau^s = 0.0$ | $\tau^s = 0.1$ | $\tau^s = 0.0$ | $\tau^s = 0.1$ | $\tau^s = 0.0$ | $\tau^s = 0.1$ |
| Total Costs | €48762 | €23214 | €43868 | €17357 | €38202 | €8814 | €30259 | €-1645 |
| Total Savings | €12874 | €6518 | €7310 | €1916 | €2516 | €0.0 | €0.0 | €0.0 |
| Battery Capacity | 0.28 MWh | 0.24 MWh | 0.24 MWh | 0.12 MWh | 0.16 MWh | 0.0 MWh | 0.0 MWh | 0.0 MWh |
| Self-Consumption | 75.9% | 75.5% | 75.5% | 73.4% | 74.2% | 69.7% | 69.7% | 69.7% |
| Degree of Autarky | 94.3% | 93.8% | 93.8% | 91% | 92.4% | 87.5% | 87.5% | 87.5% |

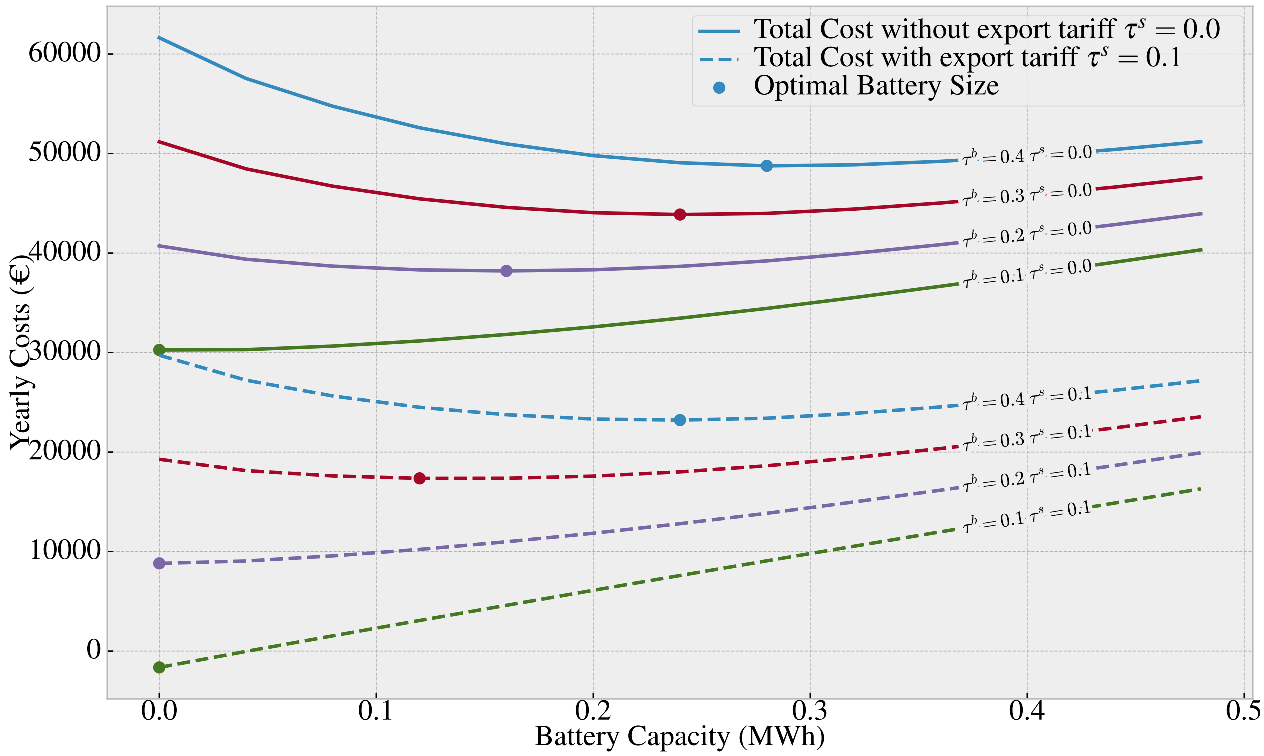



Figure 5.5: The yearly costs for the community (including battery) and the optimal battery size for different flat tariff scenarios (€ per kWh)

for the community, typically at the inflection points of the lines. We can see from the results that for most scenarios, a capacity between 0.1 and 0.3 MWh is optimal. Note that for three of the studied scenarios, the optimum is situated at a capacity of zero, meaning that it is the cheapest not to rent the battery. In these cases, the community can satisfy their needs only by using the grid. However, all these scenarios correspond to a buying price of either ten or twenty cents per kWh, which are the lowest in Europe, as can be seen in Figure 4.5. This suggests that the proposed methodology would be advantageous in most of the EU, including the Netherlands.

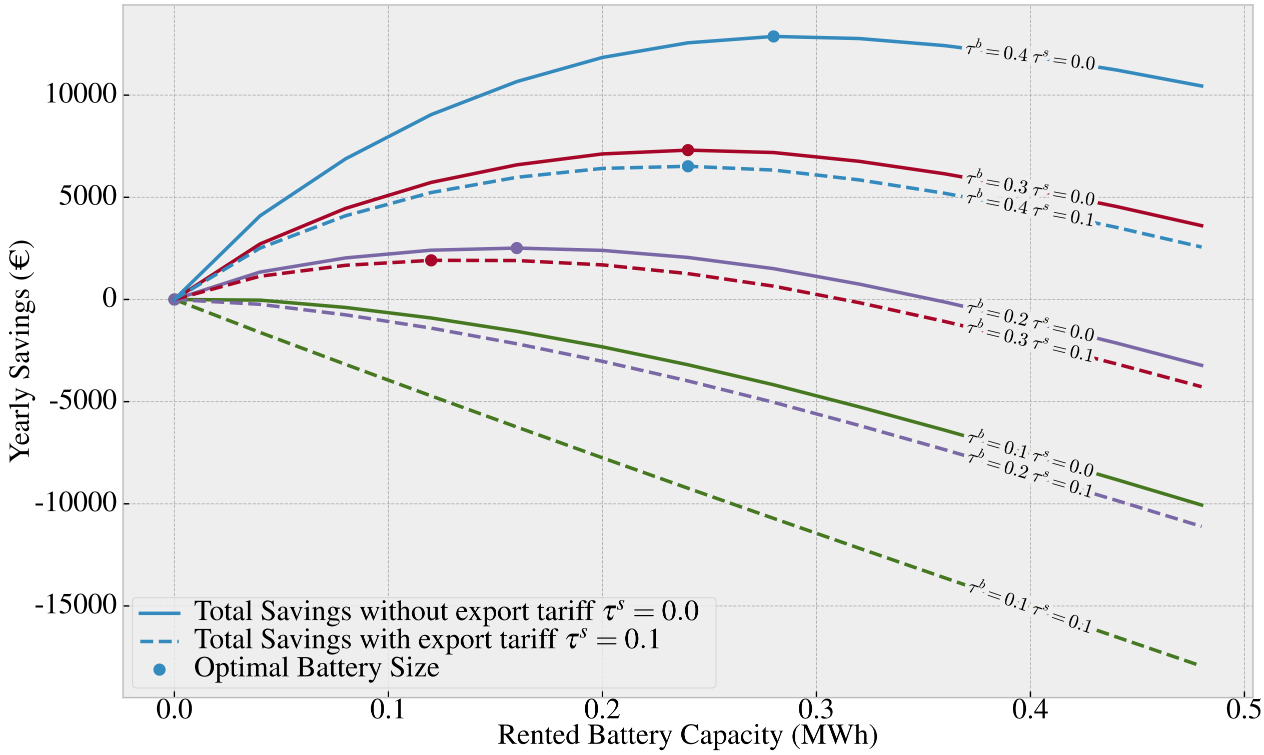



Figure 5.6: The yearly savings for the community (including battery) and the optimal battery size under different flat tariff tariff scenarios.

To further investigate this problem, we can once again compute the financial savings, which can provide a clearer view. The savings can be computed directly from the cost and can be seen in Figure 5.6 for all studied scenarios. Note that the optimal values are the same no matter the metric used, the only difference being that we either minimize or maximize, depending on the case. We can clearly see that, once again, adding ten cents to the export price has the same effect as roughly subtracting ten cents from the buying price. This explains why the optimal values between the corresponding cases are almost identical.

Table 5.1 shows the total cost, total savings, and battery capacity for the optimal case for each of the scenarios. The results show that in most cases, renting the battery is advantageous, with savings ranging from €2,516 to €12,874 for a 200-household community equipped with a 330 kW wind turbine, depending on the type of flat tariff used. The high range in the savings indicates that the feasibility of the proposed methodology highly depends on the import tariff used. The export tariff is not as important in this case, as it can be absorbed into the import price. The SC and DoA are also displayed in Table 5.1. We can see that the SC increases by as much as 6% and the DoA by as much as 7%. Note that, as mentioned in the previous section, the community starts with a relatively high SC and DoA. This, combined with the fact that the last few percentages of self-reliance are always more costly to achieve [31], makes the gains in both metrics noteworthy.

### 5.2.2 Optimal Wind Turbine Capacity for Maximizing Savings

To determine the wind turbine capacity that maximizes the savings for our community of 200 households, we can build on the previous results. As mentioned in Section 4.3.2, the scale coefficient can be used to artificially vary the wind turbine's size. We then apply the full methodology from the previous section and track the optimal cost and battery capacity for each case. The minimum cost for multiple scales is shown in Figure 5.7. Each color represents a different buying price, while the solid and dashed lines represent the cases without and with tariffs, respectively.

These results help answer subquestion RQ1(c). In the scenario without export ($\tau^s = 0$), the optimal scale falls between 1.3 and 1.7, depending on the flat tariff used. This is close to the scale of our original wind turbine, which is 1.2. Note that in the case of a flat import tariff of forty cents, the community reduces their energy bill from €300,000 to approximately €30,000, just by installing the original wind turbine. However, we observe that the community could further reduce costs by employing a larger wind turbine. In the scenario where export is allowed ($\tau^s = 0.1$), represented by the dashed lines, increasing the wind turbine size always results in higher profit. This scenario assumes unlimited exports, which is somewhat unrealistic since, in practice, curtailment will come into effect after a certain capacity is reached.

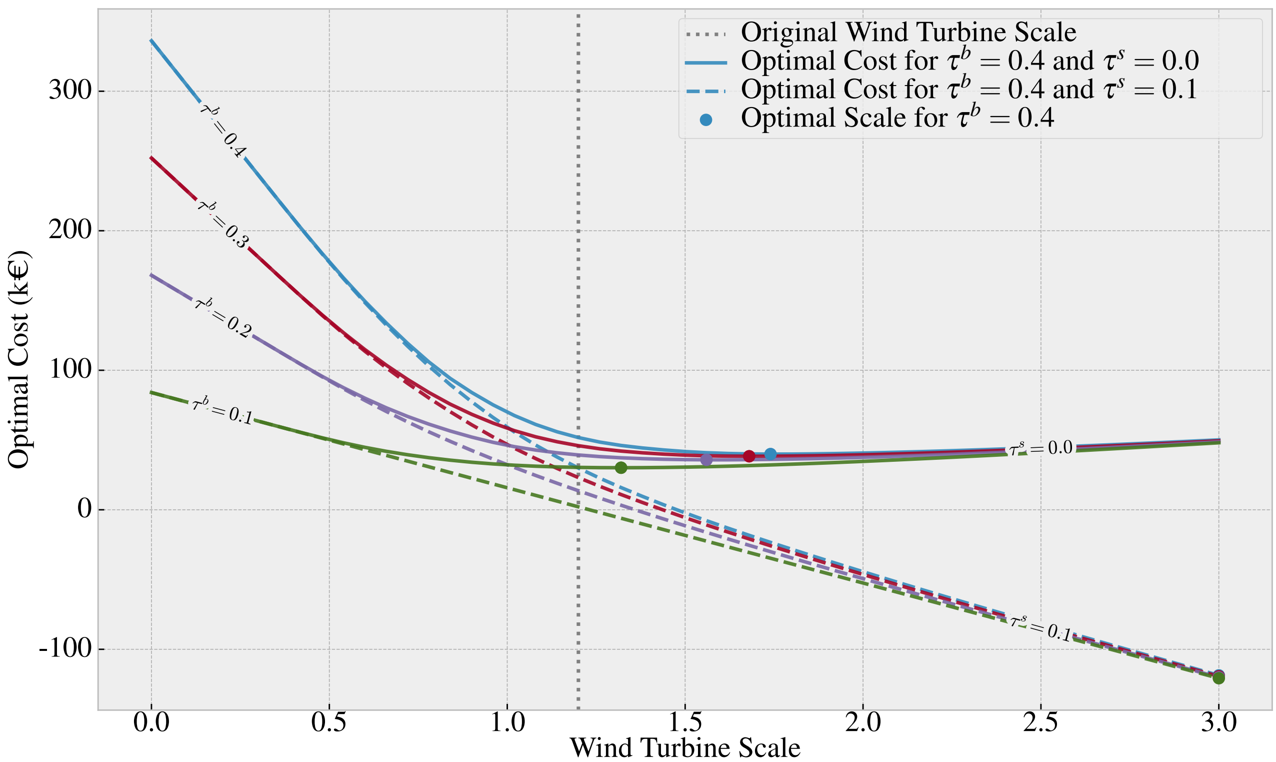



Figure 5.7: Optimal yearly cost for the community across multiple wind turbine scales under different flat tariff scenarios.

To further explore the problem, we will also examine the optimal battery capacity for each wind turbine scale. The results for the cases without and with export are separated for clarity and can be seen in Figure 5.8 and Figure A.11, respectively. The results show that the optimal battery capacity increases up to a certain point, after which it starts to decrease. Before this inflection point, the community is under-generating and needs to shift their excess generation to later times. After the inflection point, the community's demand is more frequently met instantly by the generation, requiring a smaller battery capacity.

Furthermore, the inflection point for every line is very close to the optimal scale, indicating that for the original wind turbine capacity of 1.2, the community will rent the largest battery size. However, the close alignment of the optimal scale with the inflection point is unexpected. The inflection point was anticipated to be situated around a scale of 1, where the yearly generation perfectly matches the yearly consumption. It is possible that the scaling of the power curve, as done in this section, tends to skew the inflection points towards the original scale of the wind turbine. Nonetheless, this methodology still yields valuable insights. Note that the next available wind turbine from the same manufacturer has a capacity of 700 kW [18], which would generate more than 2.5 times the yearly demand for the community. Installing such a large wind turbine for a community of only 200 households might be impractical. However, this methodology allows us to explore how a similarly sized wind turbine would affect the problem, making it a valuable tool for future planning and optimization.

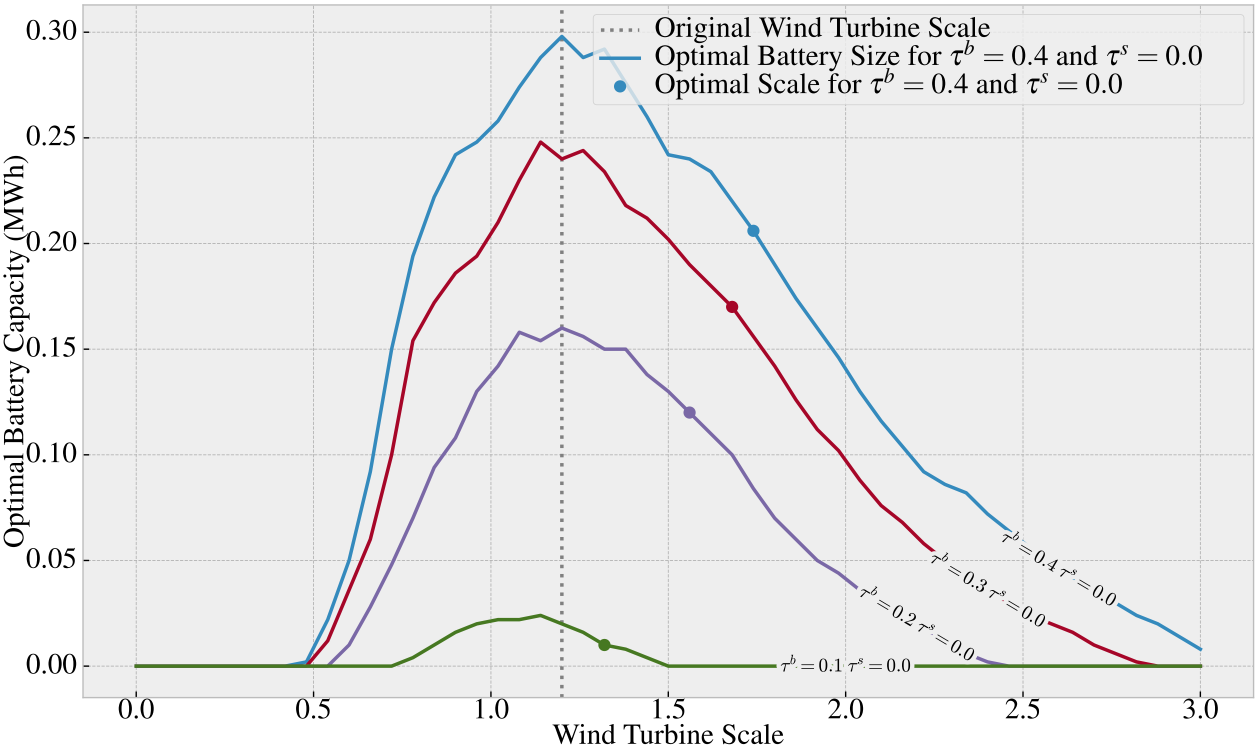



Figure 5.8: Optimal battery size for the community across multiple wind turbine scales under different flat tariff scenarios without export.

### 5.2.3 Optimal Wind Turbine Capacity for Maximizing Self-Reliance

We can also choose the size of the wind turbine such that the Self-Consumption (SC) and the Degree of Autarky (DoA) are maximized. Although we could optimize for the two metrics independently, we will see that it is better to optimize for both simultaneously, as this reduces the community's reliance on the grid the most. Both the SC and DoA were calculated for multiple scales and flat tariff scenarios. As before, the results were separated between the scenarios without and with export, and the results can be seen in Figures 5.9 and A.8. The results for all scenarios are very similar.

The SC begins at 100% in both Figures but quickly starts decreasing after a scale of 0.5. This is expected because, as mentioned in Section 4.1.4, this metric encourages the installation of small capacities. This happens because the SC tracks how much of the locally produced energy is consumed within the community. Having a smaller capacity makes the energy easier to consume. This is why increasing the capacity results in a lower SC. The results further confirm that SC is not a good stand-alone metric for deciding what generation capacity should be installed, as it will always favor smaller installations.

On the other hand, DoA exhibits the opposite behavior, starting low at 0% but quickly rising with additional capacity. This again makes sense, as the DoA measures how much of the demand is met by locally produced power. Increasing the capacity will, in turn, result in more of the demand being satisfied. Note that up to a scale of 0.5-0.6, the relationship between the scale and the DoA percentage is almost linear, i.e., a scale of 0.5 provides approximately a 50% DoA. However, beyond this point, the linear relationship no longer holds, achieving only 80% to 85% for a scale of 1. This again confirms that the last few percentages of DoA are much harder to achieve [31]. However, it is not clear from DoA alone where one should stop adding extra capacity. One could keep increasing the size indefinitely, adding smaller and smaller percentages to the DoA. However, this is not achievable in practice, as this increase requires more and more of the produced energy to be exported to the grid, as can be seen by the decrease in SC. This, in turn, increases our reliance on the grid, making congestion worse. So we can see that increasing the DoA indefinitely is not feasible.

As we can see, optimizing for either the DoA or the SC independently will always result in one of the extrema (either minimum or maximum scale) being chosen as the optimum scale, depending on the metric used, making them not useful for deciding the proper generation size that should be installed. However, we believe that the two metrics can be used together to pick a sensible generation size, one that neither imports too much nor exports too much. We can use the fact that increasing one metric decreases the other to our advantage. Optimizing for both the SC and DoA simultaneously will result in a scale that is not at one of the extrema, making this methodology viable. Furthermore, we believe that optimizing for both metrics at the same time has the most potential for decreasing congestion. Our reasoning is as follows: both metrics track grid utilization, but in different ways. SC tracks how much the grid is (not) used for exporting energy, while DoA tracks how much the grid is (not) used for importing energy. Having high percentages in both metrics would mean that the grid is minimally utilized for both import and export. This occurs at the intersection of the two lines, which is approximately at a scale of 1. For this scale, both SC and DoA are between 80% and 85%, depending on the scenario, meaning that the grid is utilized less than 20% for import and less than 20% for export.

To confirm that the joint optimum is indeed at a scale of one, a surrogate objective function can be used, one that combines both metrics into a single objective. In our case, we have looked at the minimum between the two metrics, as well as the average, which can be seen in Figure A.9a and Figure A.10a, respectively. Both figures confirm that the maximum of both metrics is achieved at a scale of roughly 1.

Lastly, we can see in Figure 5.7 that the savings difference between a scale of 1 and the scale that minimizes the cost for the community is minimal. Most of the financial gains are achieved at a scale of one. Increasing the wind turbine further will result in minimal additional earnings for the community. However, going above one will considerably decrease the SC coefficient, and in turn, our reliance on the grid. Considering all the results, we believe that a wind turbine with a scale of one would be preferable, as it allows for most of the gains to be achieved while also aiming for the highest percentages of SC and DoA. This suggests that the original wind turbine size of 1.2 was a good pick for the community studied in this thesis, even more so when considering that it has the smallest capacity offered by this manufacturer [18].

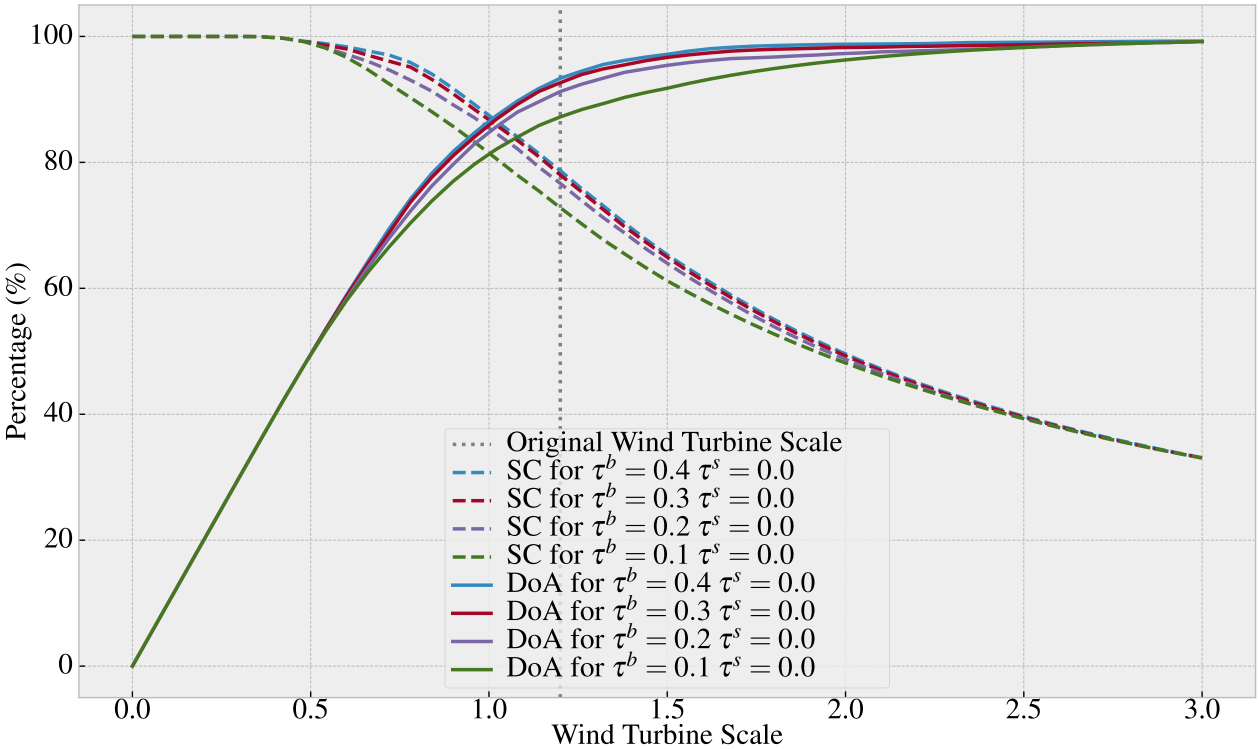


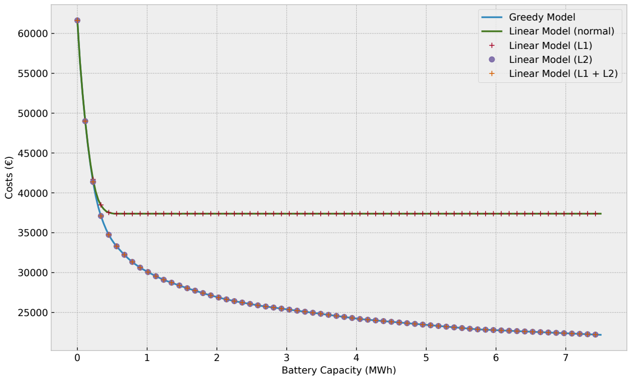

Figure 5.9: Self-Consumption (SC) and Degree of Autarky (DoA) for the community across multiple wind turbine scales under different flat tariff scenarios without export.

## 5.3 Optimal Battery Control

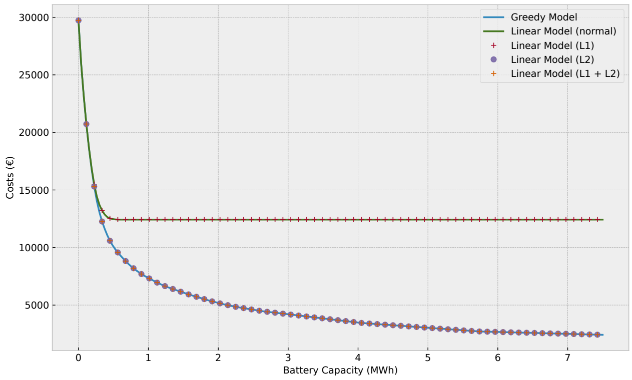
In this section, we compare the performance of greedy and linear models under three different scenarios: flat tariffs, dynamic tariffs, and market prices. For the flat and dynamic tariffs, the analysis was conducted both without an export tariff ($\tau^s = 0.0$) and with an export tariff ($\tau^s = 0.1$). Similarly, for the market prices, scenarios both with and without export tariffs were considered. For the linear model, four different variants were evaluated, covering all possible combinations of regularization costs, including the version without any regularization. The following subsections discuss the specifics of each scenario.

### 5.3.1 Flat Tariffs

First, we analyze the scenarios involving flat tariffs, both with and without export tariffs. Figure 5.10a shows the results for a constant import tariff of forty cents ($\tau^b = 0.4$ € per kWh) without an export tariff ($\tau^s = 0.0$ € per kWh). Figure 5.10b use the same import price, but a different export price ($\tau^b = 0.1$ € per kWh). In both cases, the greedy model, along with two versions of the linear model that use L2 regularization, achieved the lowest yearly cost.




(a) without export




(b) with export

Figure 5.10: Comparison between different models showing the total cost for the community for a flat tariff.

The outcomes for both scenarios align with expectations. The greedy algorithm is expected to be optimal in the context of a flat tariff, given that the buying price is above the selling price ($\tau^b > \tau^s$), which holds true for both flat tariff scenarios. Moreover, the linear models that achieved optimal costs incorporated L2 regularization, indicating its effectiveness. Lastly, the addition of L1 regularization, whether used alone or in combination with L2, did not affect the final bill, as expected.

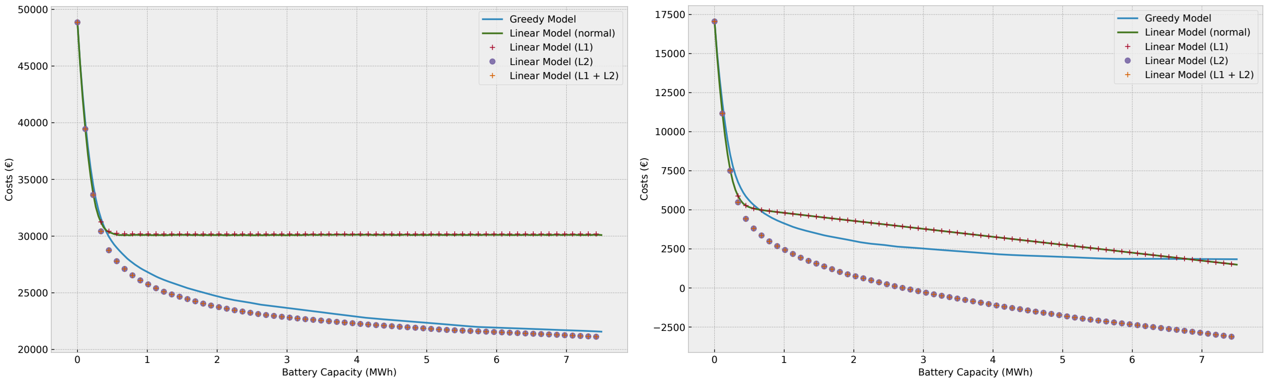
### 5.3.2 Dynamic Tariffs

In this section, we analyze the performance of the models under dynamic tariffs, considering both scenarios without export tariffs and with export tariffs. The results in Figure 5.11a depict the costs for varying battery capacities without export tariffs, while Figure 5.11b shows the costs with export tariffs.

For the dynamic tariff without export, the models incorporating L2 regularization achieved the lowest cost. The greedy model closely followed in performance but did not match the performance of the L2 models. As illustrated in Figure 5.11a, the cost reduction for the L2 regularized model becomes more significant as the battery capacity grows.

When an export tariff is introduced, the L2 regularized model still maintains the lowest cost, outperforming the greedy model more substantially compared to the no-export scenario. The difference in costs between the models increases with larger battery capacities, highlighting the effectiveness of the L2 regularization in handling dynamic tariffs, as shown in Figure 5.11b. Interestingly, this result is somewhat unexpected, as L2 regularization was initially designed with flat tariffs in mind. It was anticipated that L2 would perform poorly with dynamic tariffs, but the results indicate otherwise.

Additionally, the inclusion of L1 regularization, whether alone or combined with L2, does not lead to any cost reduction and, as expected, does not influence the final bill positively. This pattern is consistent with the results observed in the flat tariff scenarios, where the L1 regularization did not contribute to improved performance.




(a) without export

(b) with export

Figure 5.11: Comparison between different models showing the total cost for the community for a dynamic tariff.

The results clearly demonstrate that the L2 regularized linear models are the most effective in minimizing costs under dynamic tariffs, especially as battery capacity increases, while the greedy model shows competitive performance in the absence of export tariffs but falls behind when export tariffs are applied.

### 5.3.3 Market tariffs

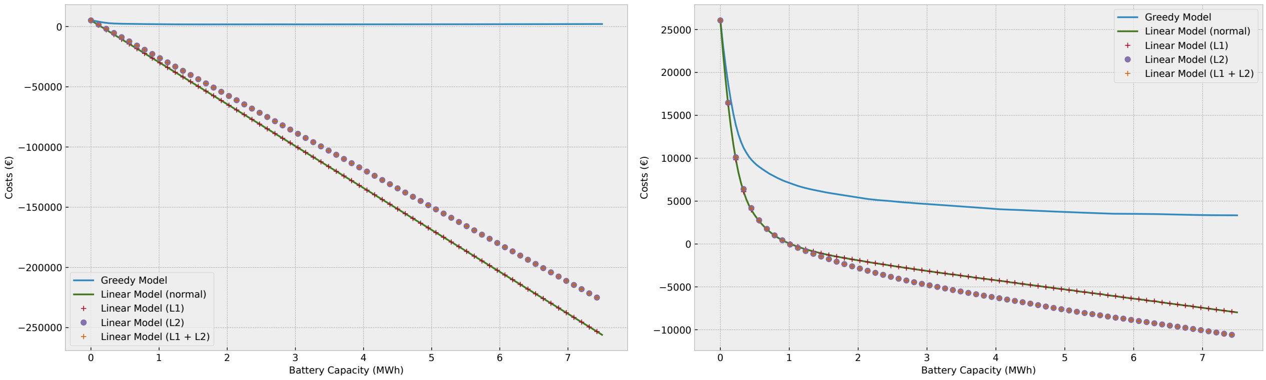
The market tariff was the last studied scenario, where day-ahead energy prices were used. Two scenarios were considered: one without any taxes and one with taxes. The results are depicted in Figure 5.12a for the scenario without taxes and in Figure 5.12b for the scenario with taxes.

In both scenarios, the greedy model lagged behind in performance. This is evident in both figures, where the costs associated with the greedy model are consistently higher than those of the linear models. This is expected, as the greedy approach is not well-suited for managing day-ahead market prices effectively.

Interestingly, in the case with taxes, the models containing the L2 regularization were once again the best performing. This was not initially anticipated, but the model also performs very well with fluctuating prices. Please note that the other linear models performed similarly up to a capacity of 1 MW, after which their performance began to diverge.

In the scenario without taxes, considered the ideal case, the linear models without L2 regularization performed the best. The simple linear model and the one with only L1 regularization achieved the lowest costs, outperforming all other models. Although the L2 regularized models outperformed the greedy model, they did not match the cost efficiency of the linear models without L2 regularization. This outcome is somewhat surprising, given that L2 regularization performed best for all other tariff types, but it aligns with our initial expectation that L2 would be less effective in the context of variable market prices.

These results highlight that for market tariffs, the addition of the L2 cost improves performance, only when taxes are applied. The findings suggest that the optimal model choice




(a) without taxes

(b) with taxes

Figure 5.12: Comparison between different models showing the total cost for the community for market prices.

is highly dependent on the specific tariff structure. Lastly, the inclusion of L1 regularization, whether alone or combined with L2, did not impact the final cost in both scenarios, either positively or negatively, exactly as in the previous cases.

# Chapter 6

# Discussion

The integration of renewable energy sources and the increasing demand for energy storage systems have driven the development of innovative methodologies to optimize the use of Battery Energy Storage Systems (BESS). This discussion explores the methodology proposed for battery owners to offer their assets as a service to energy communities, thereby enhancing their revenue streams.

In this chapter, we will delve into the implications and findings of our research on implementing Battery as a Service (BaaS) for energy communities. We will first analyze the feasibility and profitability of the proposed model. Then we will examine how different optimization methods perform under various tariff types and market conditions. By exploring the results from different perspectives, we aim to provide a comprehensive understanding of the potential benefits and challenges associated with the proposed approach.

## 6.1 Feasibility of Battery as a Service for Energy Communities

The main contribution of this thesis is the proposed methodology which enables battery owners to include energy communities as an additional revenue stream in their existing stacked revenue models. The methodology was developed around RQ1, and it is based on the fact that most BESS generate a profit by participating in various markets such as the Day-Ahead and Imbalance markets. By adding energy communities as a revenue stream, battery owners can rent out their storage capacity to communities, thereby diversifying their income sources. This approach not only helps the community lower their energy bills but also reduces their reliance on the grid.

In the Netherlands, for the year 2023, the proposed methodology showed that with a flat import tariff of forty cents, a renewable energy community of 200 households equipped with a 330KW wind turbine behind a neighborhood transformer could generate an annual profit between €6,518 and €12,874, depending on whether exporting to the grid was allowed or not. This profit can be split between the community and the company. Note that the profit calculations take into account any losses on the Day-Ahead Market. The Imbalance Market was deemed too profitable to be replaced with the proposed revenue model. Furthermore, these profits were obtained at relatively low rented capacity, 0.28MWh and 0.24 MWh respectively. This would result in around 1.5 kWh of rented capacity per household, which is much lower than what a typical household would install[42].

In order to understand why the optimal battery capacity was so low, we can take a closer look at the rental price of the battery. We showed that the battery rental price would be roughly 35 EUR per kWh of rented capacity if we consider only the Day-Ahead Market. This is roughly four times lower than the cost of a new battery. However, when we amortized the cost of the battery over 15 years, buying a new battery was much cheaper. Renting the battery for 5 years would have roughly the same cost as buying a new one. Thus, we see that the proposed model, although profitable, is not feasible in the long run, as the community will end up paying more than if they had bought a battery themselves.

However, this is typical of a rental model, where the rented commodity is cheaper in the short term but more expensive in the long run compared to purchasing the asset. Despite this, we believe that the proposed methodology still holds value, as the initial high investment cost in battery technology can be off-putting for most consumers. By opting for the proposed model, the community can optimize their energy usage without any initial investment, as the rental price is simply subtracted from the savings. Thus, although the savings might be lower, the community can still reduce their bills by renting the battery, without needing to invest anything upfront, only having to share part of the savings with the company renting the battery. This makes the proposed model very attractive, as it allows for all the risks and initial investments to be supported by the company, rather than the community.

In order to calculate the rental price of the battery, we had to look at how much the same battery capacity could earn in the energy markets. In this thesis we look at the Day-Ahead Market and Imbalance Market, For both market simulations, a linear model was used, which outputs the optimal value, usually not achievable in practice. For the Day-Ahead market, where the prices are known one day before, the profits can come very close to the optimal value. However, for the Imbalance market, this is not the case as it is highly volatile, making it hard to predict. This is why battery owners split their operation assets in a stacked revenue model between the two markets, using some internal mechanism [39]. This ensures a somewhat guaranteed smaller profit earned on the more stable Day-Ahead market while also participating in the high-risk high-reward Imbalance market. Our methodology proposes to replace some of the Day-Ahead market profits with a flat guaranteed renting fee for the community.

Another aspect that needs to be discussed is the choice of the rental price. To answer RQ1(a), we have shown the region of feasible prices and battery capacities, as seen in Figure 5.4. However, we have not determined which price should be selected, as this was not the focus of this thesis. In practice, any chosen price would result in benefits for both parties. At the maximum price, the community would not save anything but might still be incentivized by the prospect of increasing their self-reliance. At the minimum price, the company would earn exactly as much as they would from the linear models on the energy markets. However, as mentioned previously, this optimal profit is hard to obtain in practice, which means that even using the minimum rental price would result in financial gains for the company.

For subquestions RQ1(b) and RQ1(c), we have absorbed the minimum rental price into the final bill of the community. However, this does not change the problem, as the savings also encode the potential profit. It was not the focus of this thesis to decide how to split these profits between the company and the community, but this could be a possible direction for future work.

We also demonstrated how to choose the optimal size for the battery and wind generation, which is the focus of RQ1(b). For the battery, a capacity between 0.24 MWh and 0.28 MWh was found to be optimal in the Netherlands for a typical energy community of around 200 households, depending on whether export was allowed or not. As expected, higher energy prices or not having export possibilities increase the required battery size. Unexpectedly, the battery can lower the overall bill of the community even for a small electricity tariff of 0.2 cents, which would make the proposed model viable across Europe.

Finally, we have also looked at how the proposed methodology can be used to answer RQ1(c), which aims to determine the optimal wind capacity that should be installed. We examined this problem from two perspectives: minimizing cost and maximizing self-reliance. Minimizing cost results in an optimal wind turbine with a higher capacity than the one originally installed. In the scenario where export was not allowed, the lowest cost was achieved by a wind turbine that generates 1.4-1.6 times the yearly demand of the community. Unexpectedly, increasing the wind turbine capacity results in a smaller optimal battery capacity. In the scenario where export was allowed, it was found that increasing the wind turbine size always increases profits. However, this is somewhat unrealistic, as unlimited exports would not be feasible and would create congestion problems.

To minimize congestion, we proposed optimizing the scale such that the self-consumption (SC) and degree of autarky (DoA) are maximized. Optimizing for the two metrics independently is not feasible, as it will always result in one of the extrema. However, we can use the fact that increasing one metric decreases the other, and optimize for both metrics simultaneously. This, in turn, reduces our reliance on the grid the most, both for importing and exporting. We found that this results in an optimal scale of around 1. At this scale, both the SC and DoA are above 80%, meaning that the grid is utilized at most 20% for satisfying the demand and at most 20% for exporting excess energy. Furthermore, increasing the wind turbine capacity beyond a scale of 1 does not significantly increase the gains for the community. Therefore, we believe that an optimal generation scale would be around 1, where the community's reliance on the grid is minimized while also achieving most of the financial gains associated with installing a wind turbine.

## 6.2 Model Performance Across Different Tariff Types

In order to answer RQ2, we have analyzed how different models compare with each other on different tariff types. The results indicate that the greedy algorithm performs surprisingly well, even when prices fluctuate. However, this strategy can be further refined if the energy prices are accounted for.

For the flat tariff, which corresponds with RQ2(a), the greedy model outperformed the simple linear model. We observed that this discrepancy is caused because the linear model discharges the battery at the end of the day. This happens because the linear model does not have access to the loads for the next day due to its limited time horizon, so it always sells the energy to maximize daily profits, but not yearly profits. To address this problem, we introduced the L2 regularization cost, which penalizes the model based on the empty capacity at the end of the day. The linear model equipped with the L2 regularization performed the same as the greedy model. The L2 regularization was inspired by the heuristic used in the greedy model, which always prioritizes battery use. The results indicate that this strategy is optimal in the case of a flat tariff, as both the greedy model and the linear model incorporating it performed the best.

In the case of the dynamic tariff, which corresponds with RQ2(b), surprisingly, the same strategy performed the best. For this situation, the linear model that employed the L2 regularization had the best performance, although the greedy model's performance was close behind. Furthermore, the greedy model performed significantly better than the linear model without the L2 regularization costs. These results indicate that, although the one-day time horizon of the linear model allows it to better optimize the schedule, it is the greedy strategy that generates the most revenue in this case. However, accounting for the energy prices can further refine the schedule, unlocking additional savings.

In the case of the market tariffs, which are the prices from the day-ahead market and correspond with RQ2(c), the linear models always performed better than the greedy model, regardless of whether L2 was applied or not. This indicates that in the context of energy markets, the greedy strategy is no longer the most profitable. However, it is interesting to note that when transport tariffs are applied, the linear model with L2 regularization outperforms the simple linear model. This suggests that although the greedy strategy is not beneficial as a stand-alone strategy, it can still be applied in conjunction with the linear model to further increase profits.

Lastly, we observed that the linear model produces schedules with many charging and discharging cycles, without any obvious benefits. We explained this through the fact that the model may not adequately account for battery wear. To steer the linear model towards a solution with the least battery wear, we also introduced the L1 regularization cost, which penalizes the model for each charging and discharging cycle. We have shown that in all cases, adding the L1 regularization, either alone or together with L2, does not change the final costs, while drastically reducing battery wear.

# Chapter 7

# Conclusions and Future Work

This chapter provides an overview of the main contributions, reflects on the results, and draws conclusions. Finally, it discusses some ideas for future work.

## 7.1 Contributions

The main contribution of this thesis is the development of a methodology for determining a price, or more specifically, a price range, for renting battery capacity to energy communities. We demonstrated that the proposed stacked revenue model can be advantageous for both the community and the company across multiple tariff types. We extended this methodology to also find the optimal battery capacity and generation scale for the community such that the total cost is minimized. However, we have shown that cost is not the best metric for optimizing the size of the generation, as it does not account for grid congestion. In this regard, we proposed that both the self-consumption coefficient and the degree of autarky (DoA) can be used together to optimize the size of the installed wind turbine, providing the community with the least reliance on the grid and, in turn, avoiding congestion problems.

We have also compared the greedy model against the linear model across multiple types of tariffs to study how the battery should be controlled. Two regularization costs were added to the linear model in an effort to steer the schedule toward more desirable solutions. The first regularization cost, L1, was successful in reducing the number of cycles performed by the battery without increasing the final cost. The L2 regularization exceeded expectations and significantly improved the performance of the linear model.

However, some caveats should be noted. We have not considered the cost of any additional infrastructure, such as power lines, transformers, etc. It is assumed in this thesis that the battery is situated in the vicinity of the energy community, without the need for costly additional transmission or distribution infrastructure. This might not be true in real-world cases. We believe that adding these costs will change the optimal generation scale when the savings are maximized. For all other calculations, adding these costs would be similar to increasing the price of the wind turbine, having little impact on the final analysis. Furthermore, scaling the wind turbine as done in this thesis does not work in the real world, as the power curve is specific for each turbine. However, usually, higher-capacity turbines are more efficient, so our study might underestimate the capabilities of the scaled wind turbine, making the real-world case even more viable. Nonetheless, the size of the wind turbine was not optimized directly using the cost, which means that the points mentioned above are of little concern.

## 7.2 Conclusions

The results show that it is feasible for battery owners operating a stacked revenue model to replace some of the profits from the Day-Ahead market with the newly proposed revenue source of renting part of the battery to energy communities. The proposed methodology is profitable across a wide range of tariffs and can achieve equal or better earnings than the Day-Ahead prices in the Netherlands using the historical prices from 2023, up to certain capacities. We have shown how this methodology can be extended to calculate the optimal renting sizes. In the case of a flat import tariff of forty cents per kWh, a community of 200 households equipped with a 330 kW wind turbine behind a neighborhood transformer would obtain maximum savings for a capacity of 0.24 MWh and 0.28 MWh, depending on whether the community was paid for their exported energy or not. The annual savings associated with these capacities are €6,518 and €12,874, respectively. These capacities will also result in the SC and DoA increasing by 6% and 7%, respectively.

We have also shown that using cost alone for optimizing the generation capacity can lead to oversizing, which in turn increases the community's reliance on the grid. The SC and DoA are much better metrics in this regard. Optimizing the generation size with both metrics in mind results in an optimal scale of 1, which means that the wind turbine's output will be equal to the community's yearly demand. This size results in both SC and DoA being over 80%, while also achieving most financial gains in the process.

We have also shown that the greedy model performs optimally in the case of the flat tariff, outperforming the linear model with a one-day horizon. Surprisingly, this model also performs well on dynamic prices, indicating that it is a viable strategy for multiple scenarios. The linear model with a one-day event horizon generally performed poorly, producing suboptimal results. A regularization cost called L2 was introduced to improve the behavior of the linear model by forcing it to charge the battery at the end of the day. This component significantly improved the behavior of the linear model in all but one scenario. All of this indicates that the greedy behavior employed by the best-performing model is a valid strategy even for the linear optimization model. Lastly, we introduced a regularization cost L1 that minimizes battery usage while not affecting the optimality of the solution. This cost was successful in minimizing wear while not affecting the cost in any scenario.

## 7.3 Future Work

This thesis opens the possibility for multiple future areas of research. On one hand, the methodology could be extended to consider other revenue streams beyond the Day-Ahead Market and Imbalance Market. This would be relatively easy to achieve for any revenue streams where the (potential) profit can be easily computed. BESSs are currently generating profit by offering a wide range of services, so there is clear potential for finding more that can be replaced with the proposed revenue stream. On the other hand, the differences between the greedy and linear models could be further studied. The regularization functions used in the linear model contain parameters that could be tuned to achieve better results in different types of markets. In this study, the same value was used for every scenario, but some scenarios might work better with specific values.

Furthermore, in the case of L2 regularization, the parameter indicates the price under which the model will import energy with the sole purpose of charging the battery, accounting for any future loads. It would be interesting to incorporate this behavior into the greedy model, using the same parameter. An interesting idea would be to hyper-tune the parameter using the linear model and then apply it to the greedy model. The greedy model does not need predictive demand and generation curves to be known in advance, while the linear model does. Having a greedy model incorporating this parameter would mean that the regularization could be deployable in practice.

Lastly, we could explore how to predict generation and demand curves using machine learning. Incorporating the uncertainties of the predictions inside our linear model could control the battery in a way that maximizes the expected returns. This would make the linear models deployable in practice.

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# Appendix A

# Extra Experimental Results

This appendix includes additional figures that support our findings. These figures provide further insights into the various scenarios analyzed, offering a deeper understanding of the studied problem.

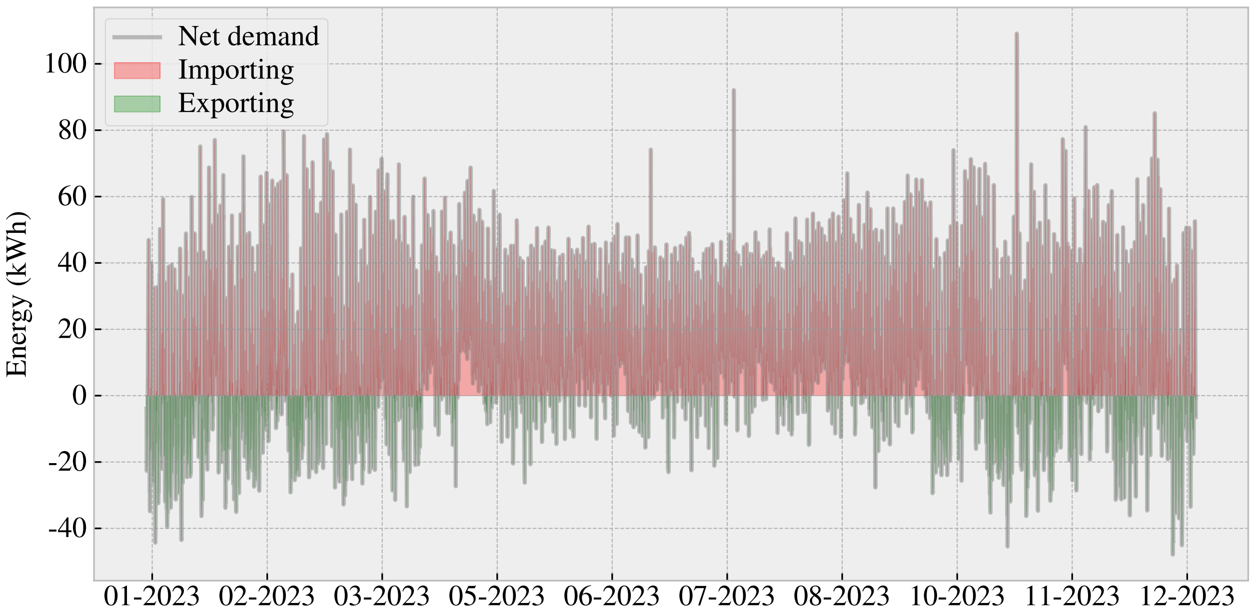



Figure A.1: The half-hourly net generation ($g_i - d_i$) for a community of 200 households, using an artificial generation scale of 0.75

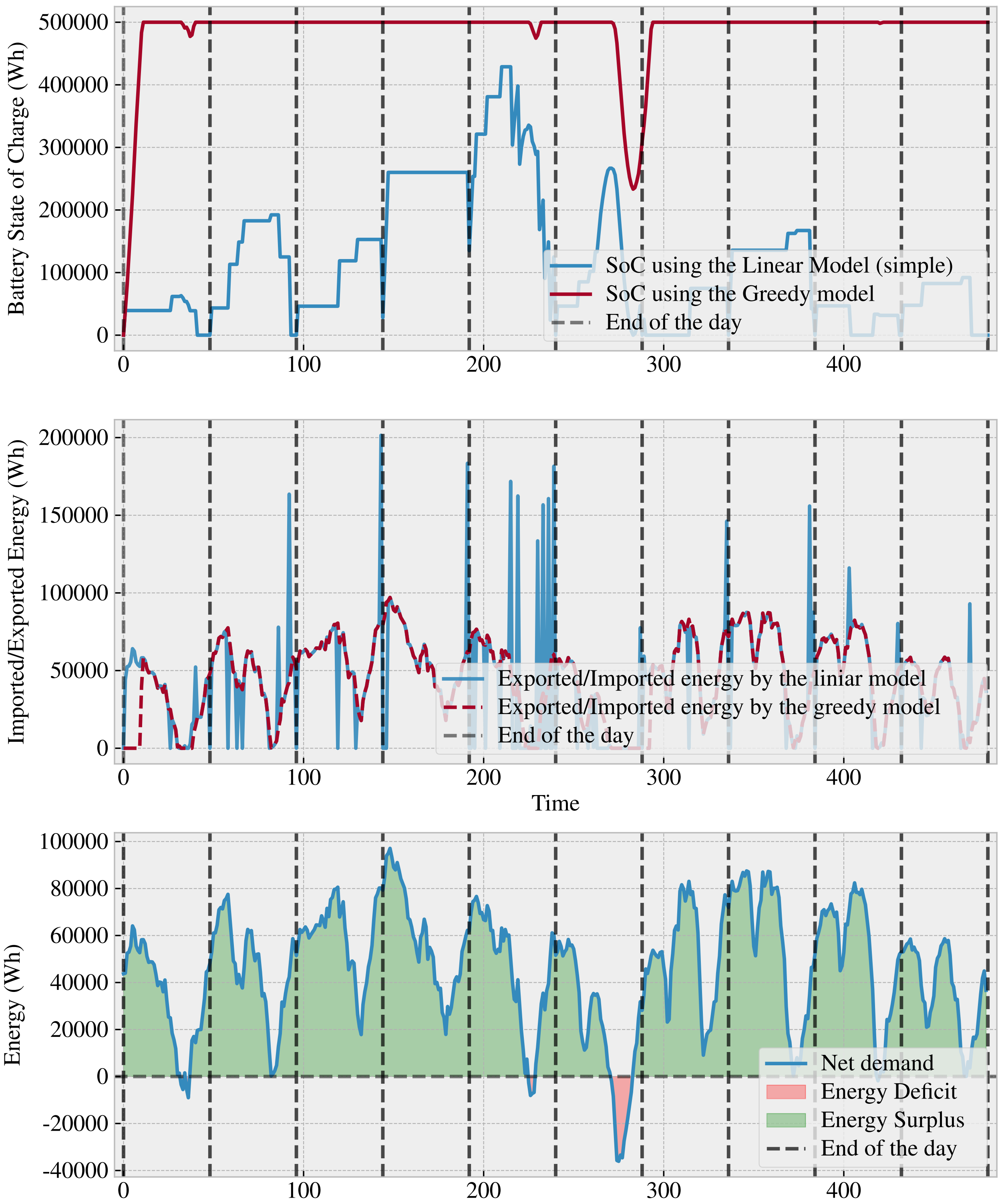



Figure A.2: Comparison between the schedules produced by the greedy model and the linear model (simple), showing the state of charge (top), imported/exported energy (middle), and net generation (bottom).

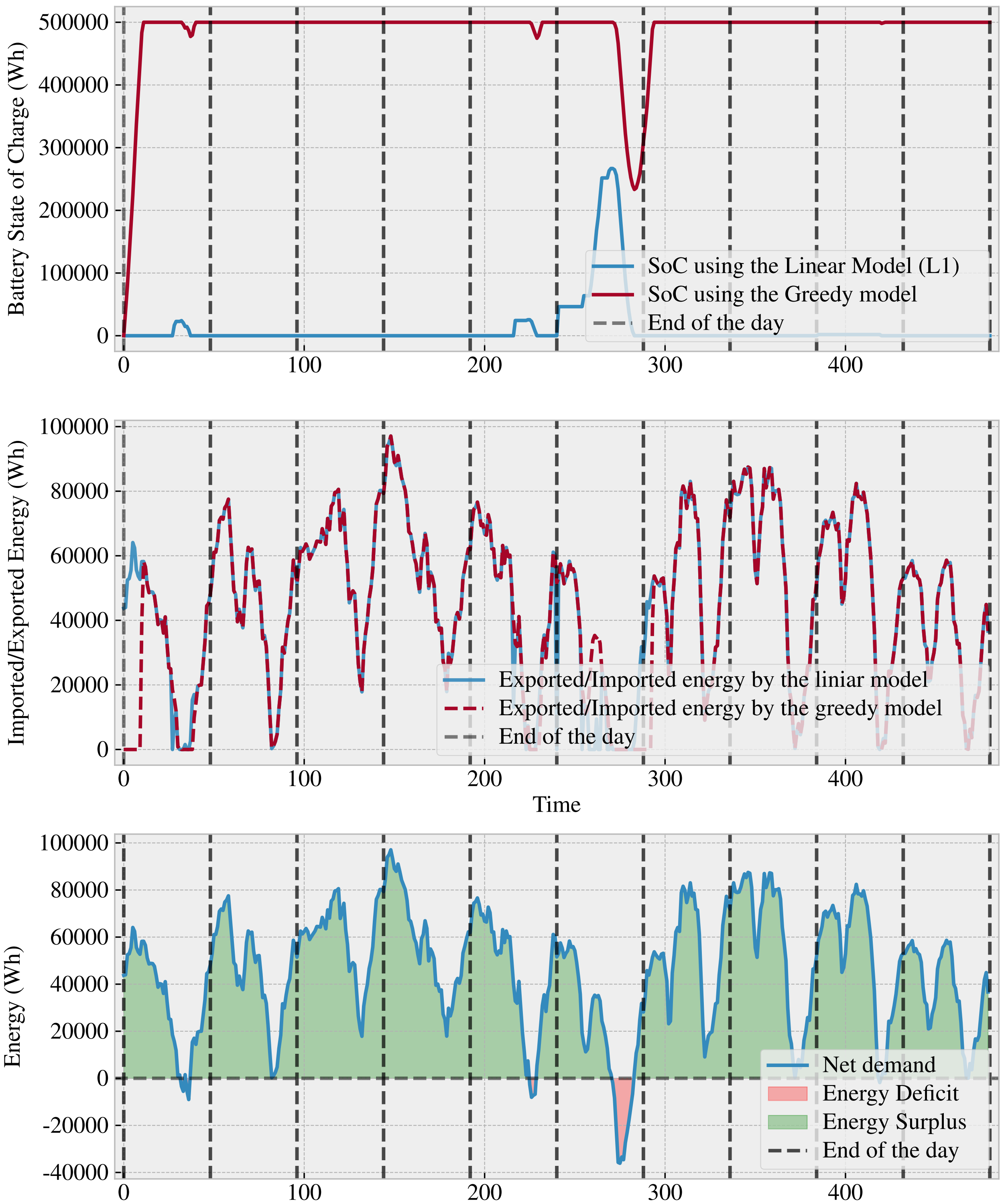



Figure A.3: Comparison between the schedules produced by the greedy model and the linear model (L1), showing the state of charge (top), imported/exported energy (middle), and net generation (bottom).

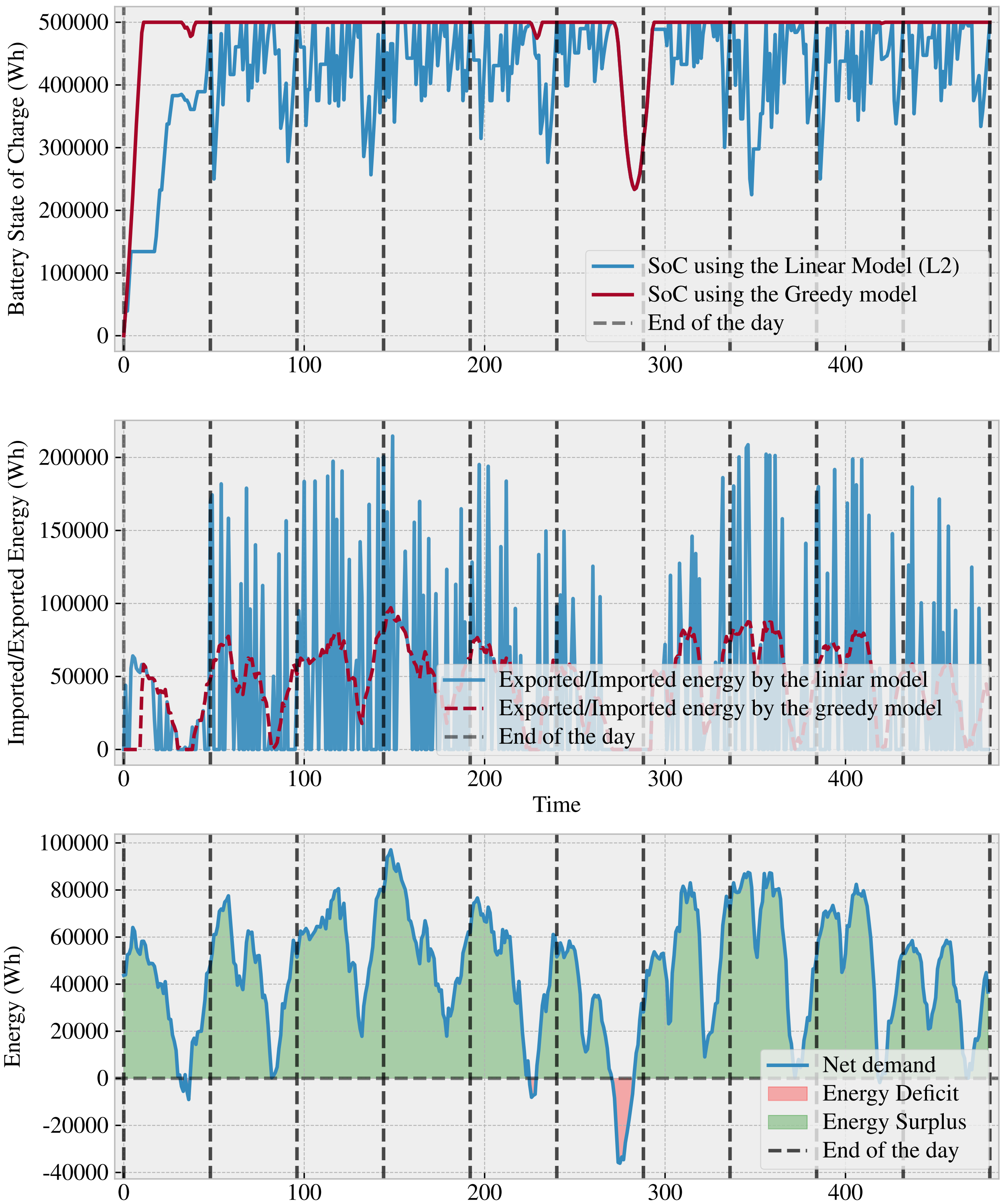



Figure A.4: Comparison between the schedules produced by the greedy model and the linear model (L2), showing the state of charge (top), imported/exported energy (middle), and net generation (bottom).

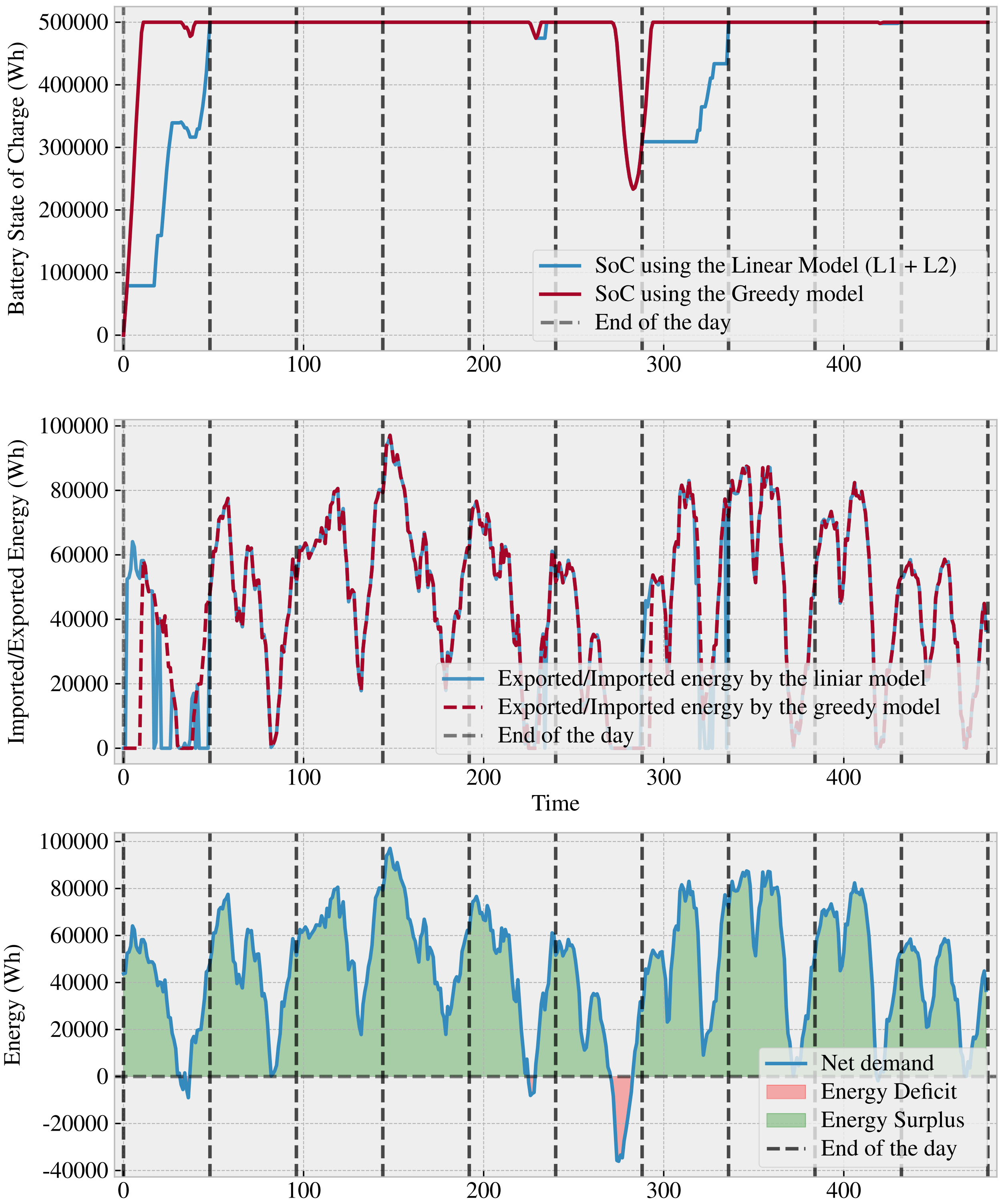
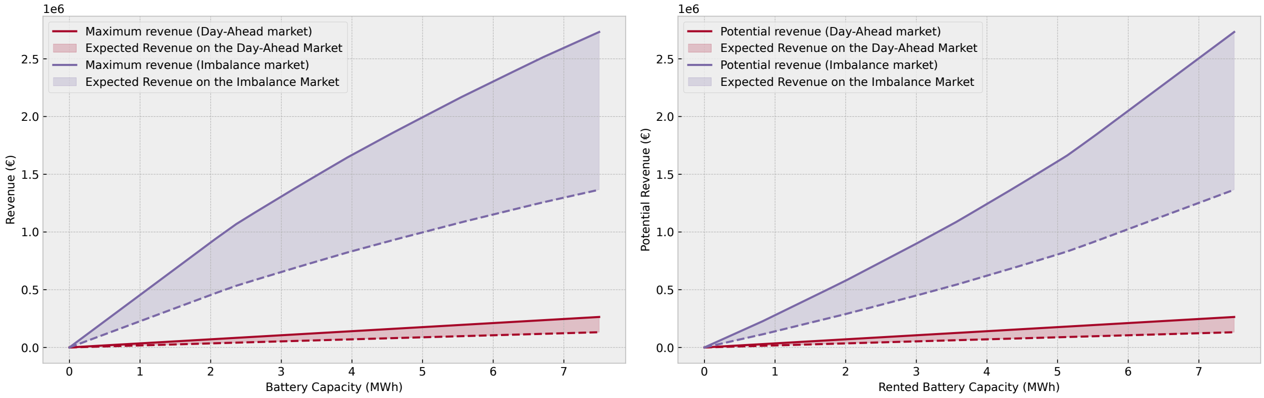



Figure A.5: Comparison between the schedules produced by the greedy model and the linear model (L1 + L2), showing the state of charge (top), imported/exported energy (middle), and net generation (bottom).




(a) Maximum and expected revenue on the Imbalance and Day-Ahead market for different battery capacities.

(b) Potential Revenue on the Imbalance and Day-Ahead market for different battery capacities.

Figure A.6: Big Title

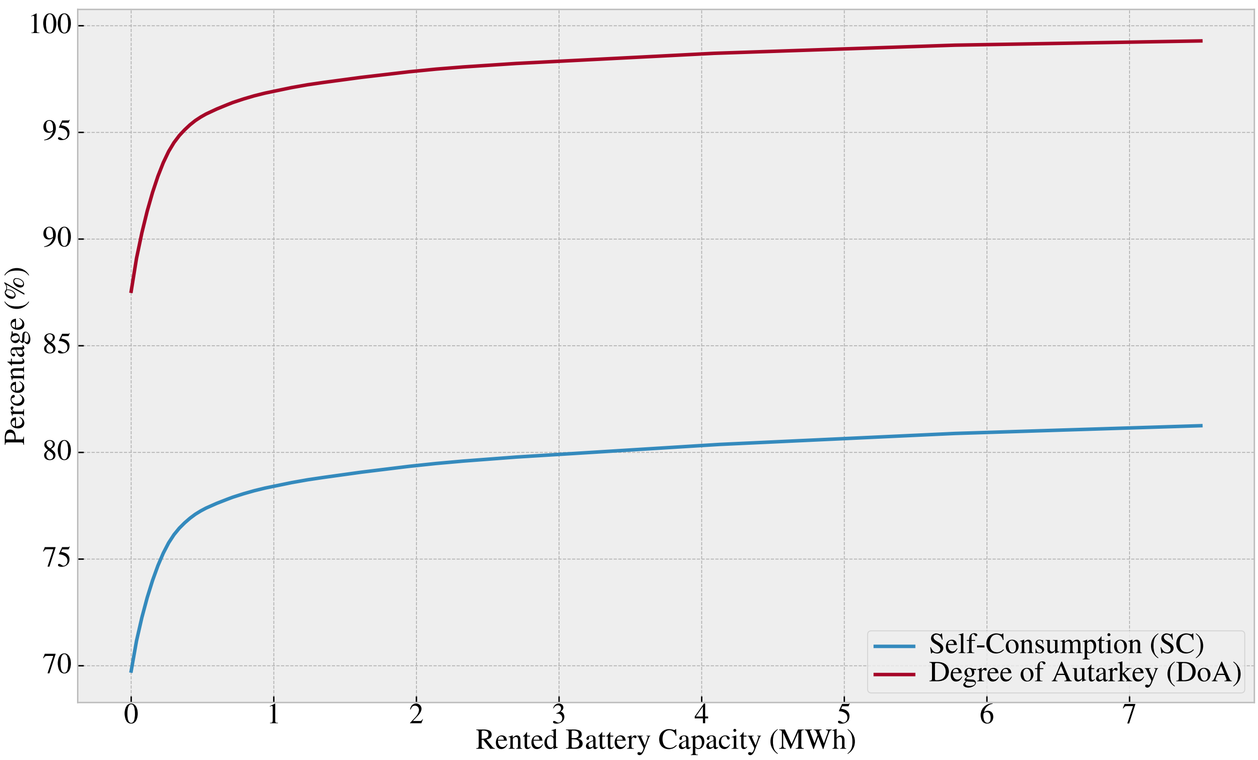



Figure A.7: Self-Consumption (SC) and Degree of Autarky (DoA) for the community across multiple battery capacities.

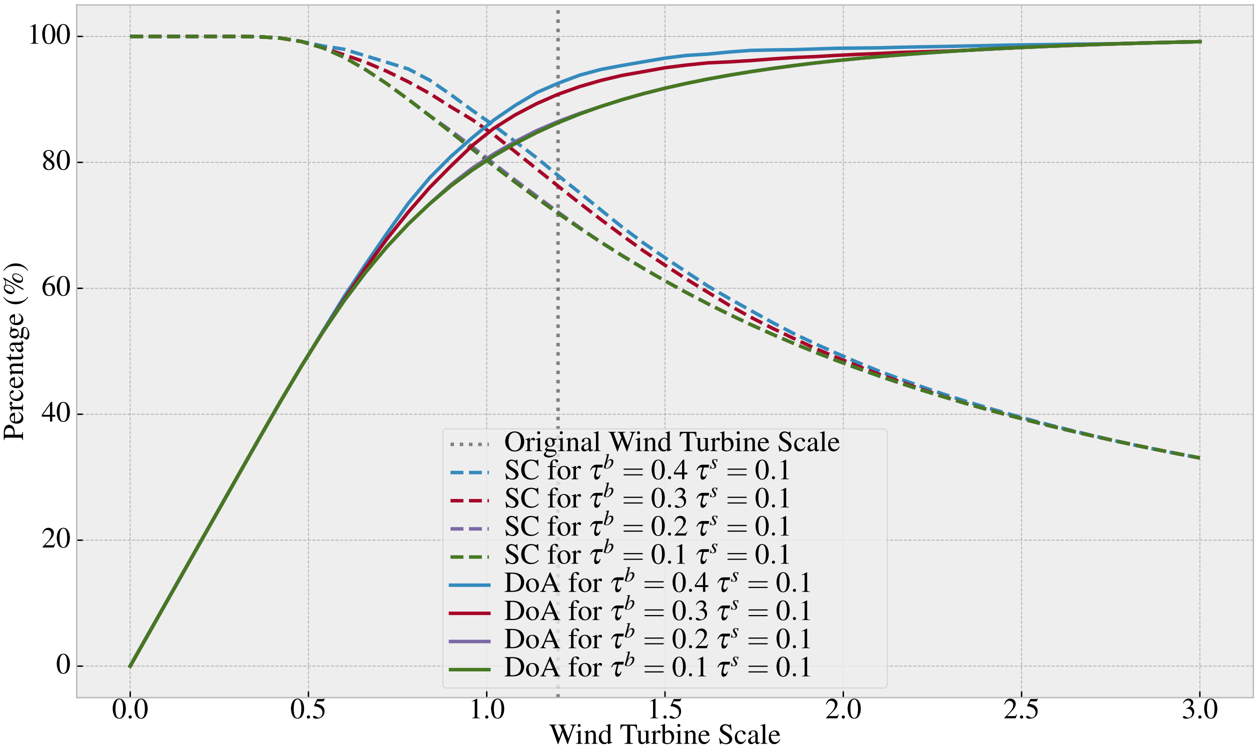
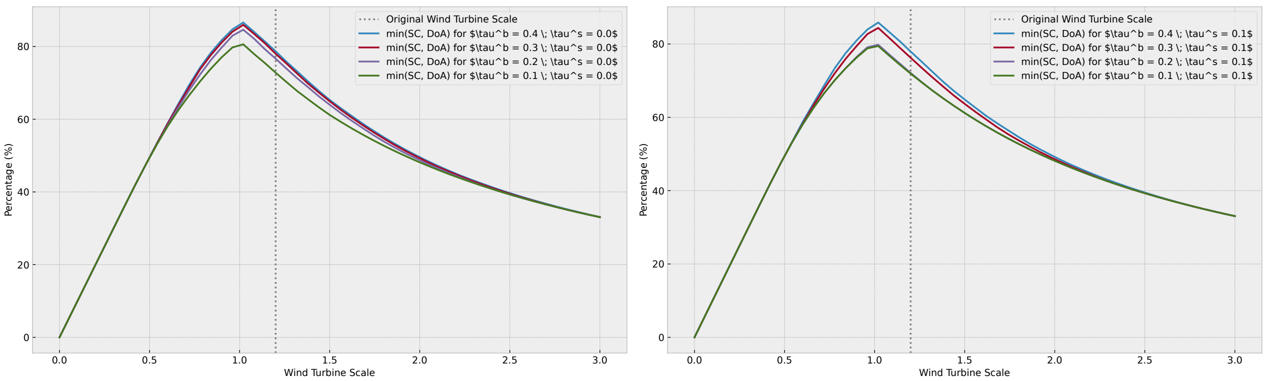


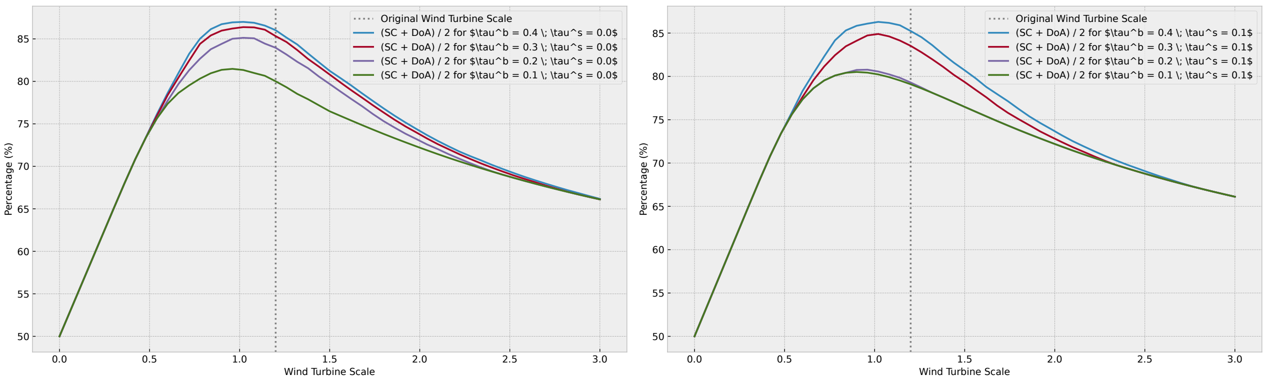

Figure A.8: Self-Consumption (SC) and Degree of Autarky (DoA) for the community across multiple wind turbine scales under different flat tariff scenarios with export.




(a) Flat tariff without export.

(b) Flat tariff with export.

Figure A.9: Minimum between Self-Consumption (SC) and Degree of Autarky (DoA) for the community across multiple wind turbine scales under different flat tariff scenarios.




(a) flat tariff without export

(b) flat tariff with export

Figure A.10: Average between Self-Consumption (SC) and Degree of Autarky (DoA) for the community across multiple wind turbine scales under different flat tariff scenarios.

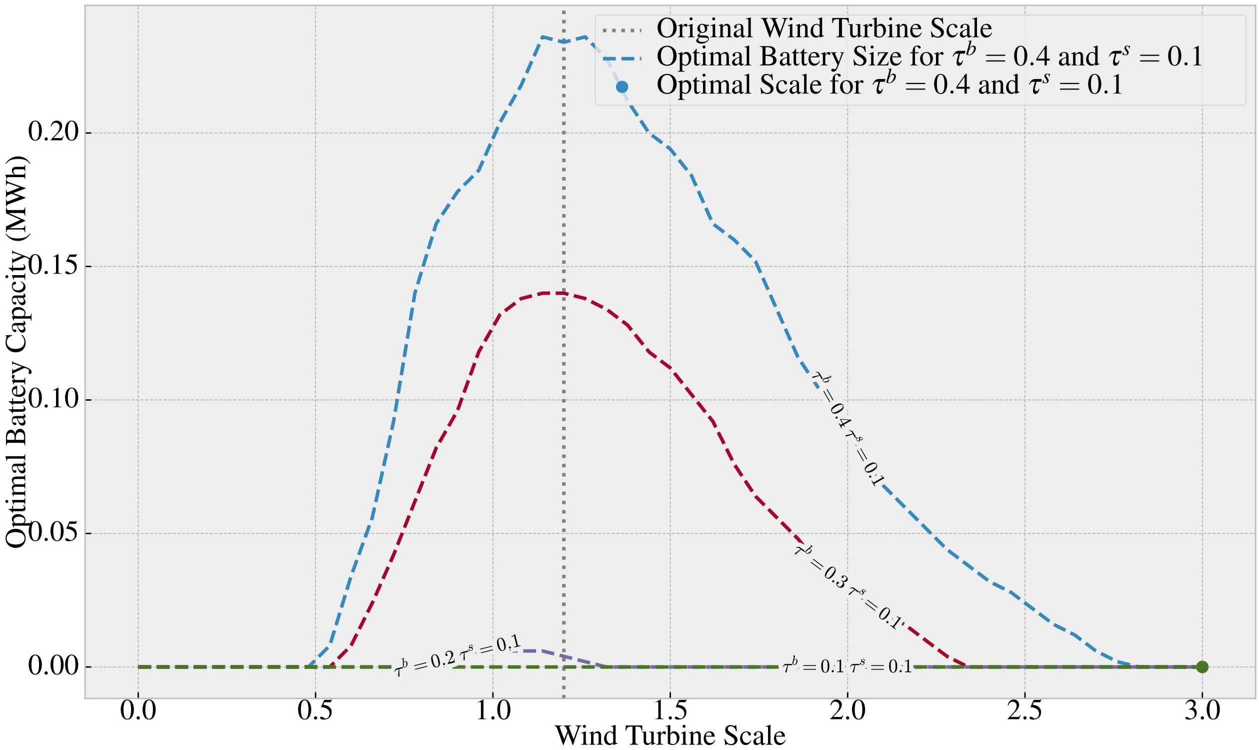



Figure A.11: Optimal battery size for the community across multiple wind turbine scales under different flat tariff scenarios with export.