DTU Wind and Energy Systems

Investigating the integration of Vehicle-to-Grid (V2G) technology in energy communities with private solar panels and electric vehicles

Mikkel Mørkeberg Wagner & Bjørn Jacobi Höyer

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ECTS: 20

Education: Bachelor of Science

Supervisors:

Francesco Pastorelli
Tim Unterluggauer
Mattia Marinelli
DTU Wind and Energy Systems

Carsten Sass Husum
Lars Hansen
COWI

Remarks:
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Technical University of Denmark
Department of Wind and Energy Systems
Frederiksborgvej 339
DK-4000 Roskilde
www.wind.dtu.dk

Abstract

This thesis investigates how electricity cost in an energy community with Photovoltaic (PV) energy production is affected by including electric vehicles (EVs) with Vehicle-to-building (V2B) technology. Utilizing a detailed optimization model, the performance of the V2B system is compared to a stationary battery system, and a smart charging system (V1G). The optimization model builds on real driving data, PV generation, electricity consumption and electricity cost, ensuring a realistic model. The optimization was conducted over a week in summer and a week in winter to examine scenarios with low and high PV generation. The results rely on a wide range of assumptions to help the construction of the model. These assumptions can potentially have inflated the results but not significantly enough to change the overall conclusion of this thesis.

The results indicate that the V2B scenario clearly outperforms the stationary battery and V1G system in reducing electricity costs. Compared to the stationary battery, the V2B system saves 19,183 Kr. and 19,125 Kr. during a week in winter and summer, respectively. The savings are even larger when compared with the V1G scenario, where savings are 62,703 Kr. and 65,025 Kr. Scaling to a full year, each EV in the V2B system results in a yearly saving of 5,773 Kr. when compared to the V1G system. These findings suggest that integrating V2B technology in energy communities can provide significant economic benefits and enhance self-consumption of PV.

Beyond economic savings, the integration of V2B technology in energy communities can lead to environmental benefits. The V2B technology assists in filling the gaps in fluctuating renewable energy production, reducing reliance on more consistent producing fossil fuels. The V2B technology's ability to store and redistribute energy supports the transition to a more CO2-neutral world.

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Acronyms

AC	Alternating Current
BMS	Battery Management System
CAPEX	Capital Expenditure
DC	Direct Current
Kr.	Danish Krone
DSO	Distribution System Operator
EV	Electric Vehicle
NPV	Net Present Value
OPEX	Operational Expenditure
PV	Photovoltaic
SOC	State of Charge
SOE	State of Energy
V1G	Unidirectional Smart Charging
V2B	Vehicle to Building
V2G	Vehicle to Grid
V2H	Vehicle to Home
V2X	Vehicle to Everything

Contents

1 Introduction

In the mission to combat climate change, the world is increasingly turning to innovative solutions that not only mitigate environmental impact but also transform energy consumption patterns. Sustainable energy production, such as photovoltaic (PV) energy and wind energy, produces energy less consistently compared to conventional power plants [1]. To maintain the balance between production and consumption, demand either has to shift towards production [2], or some of the excess production needs to be stored and deployed when demand exceeds production [3]. While some demand can potentially be shifted to match production, household demand is largely determined by its inhabitants. People have many routines, such as going to work and sleeping at specific times, resulting in well-defined demand patterns that are difficult to shift. Therefore, to address this challenge, storage solutions appear to be the best response to fulfilling household demand with sustainable energy production.

One obvious storage solution is a stationary battery that can charge when demand is low and discharge when demand is high. However, batteries are expensive, and widespread implementation will only be feasible with a strong economic incentive. In addition to stationary batteries, Electric Vehicles (EVs) have large batteries and cars spend only 4% of their time driving [4], resulting in a lot of downtime. An emerging technology, bidirectional charging, capitalizes on this downtime by essentially working as a stationary battery when parked, providing services to the grid (V2G), households (V2H), or other entities (V2X). The EV is then used for multiple purposes, which could provide more economic incentive compared to the stationary counterpart.

To explore these options further, this thesis investigates a stationary battery system and a Vehicle-to-Building system (V2B), where EVs can charge and discharge to surrounding buildings and households. These two scenarios are compared to a baseline scenario without a stationary battery and where the EVs can only charge and not discharge. In this baseline scenario, the EVs are assumed to "smart charge," meaning they can charge at any rate within a boundary and when it is optimal price-wise. This scenario will be referred to as V1G. The V1G charging strategy will also be used for the EVs in the stationary battery system. These scenarios all take place in Fælledby, which is a residential area currently being developed on Amager Fælled in Copenhagen [5].

The primary objective of this thesis is to quantify the economic advantages of using V2B technology in comparison to a stationary battery system and a V1G system. Given that V2B technology is relatively new and not widely adopted. This thesis aims to offer insights into how it can improve energy self-consumption and lower expenses once it becomes more widely adopted. The EV market is rapidly growing in Denmark [6], and at the current growth rate, it is expected that there will be over 2,000,000 EVs in Denmark by 2035 [7]. Therefore, the setting for this study is 2035. This increase in the total EV fleet means more vehicles can participate in V2B services, and therefore provides a more accurate picture of the benefits V2B can offer once the technology is more mature and implemented.

1.1 Scenario introduction

This section provides a brief overview of the V2B, V1G, and battery scenarios used in this thesis. In total, six simulations were conducted: two for each scenario, simulating both summer and winter conditions to observe system performance under high and low PV generation periods. The optimizations turned out to be quite complex, resulting in simulations being limited to one week at a time.

Vehicle-to-Building (V2B): This scenario allows for bidirectional energy flow, enabling electric vehicles to draw energy from the grid or energy community and also return energy to it. Unlike stationary storage, the available storage capacity in the V2B scenario fluctuates throughout the day as the EVs make their journeys.

Smart Charging (V1G): This scenario involves one-way charging strategies where electric vehicles adjust their charging schedules based on grid demands. It utilizes the batteries of electric vehicles to absorb excess grid energy during low-demand periods.

Stationary Battery Storage: In this scenario, batteries are used independently of vehicles to store energy. These batteries have a fixed maximum capacity and can store surplus energy from the PV for later use, helping to manage energy supply while still using smart charging for EVs.

1.2 Literature review

This section reviews studies optimizing bidirectional charging and EVs.

Source [8]: Optimized V2G where EVs performed ancillary services to the grid. This included real-world driving patterns, and the optimization goal was achieving the highest monetary value. The EVs were not connected to an energy community and did not include local production.

In [9], the impact of utilizing V1G and V2G cars in a macro energy system was reviewed. Five energy systems were examined with gradually increasing amounts of renewable energy. In these five systems, the study altered the number of V1G and V2G capable EVs and optimized the system for the overall electricity cost.

Lastly, [10] analyzes a system of five households and four EVs connected in an energy community. The article used real-world driving data, and the optimization revolved around maximizing own PV consumption for the analyzed day.

Article	Real-world driving data	Scale	Energy community	Bidirectional charging	Local energy production	Optimization objective	Optimization time frame
[8]	Yes	7163 EVs	No	Yes	No	Price	1 Year
[9]	Yes	Macro	No	Yes	No	Price	1 Year
[10]	Yes	4 EVs	Yes	Yes	Yes	PV consumption	1 day
Fælledby	Yes	574 EVs	Yes	Yes	Yes	Price	2 weeks

Table 1: Comparable literature

This thesis bridges some gaps by analyzing a medium scale of EVs. In [8] and [9], the systems were very large and focused on grid-scale implementation. In contrast, [10] is a small-scale system, which might lose some of the benefits when running a larger operation. The purpose of this thesis is to investigate how EVs capable of V2B operate in a medium-sized system with local energy production. Compared to [10], Fælledby utilizes the energy community better, as more EVs are operating on it.

1.3 Outline

In this thesis, the charging and discharging strategies of the V1G, stationary battery, and V2B scenarios are optimized to achieve the lowest electricity price.

Chapter 2 outlines the basics of bidirectional charging. Additionally, it describes the workings of an energy community and how EVs with bidirectional capabilities can play a role in this.

Chapter 3 describes Fælledby in detail, including both the planned energy system and the estimated driving patterns of the future inhabitants.

Chapter 4 provides an overview of all the assumptions made in the optimization models and describes how the optimization models were initiated.

Chapter 5 analyzes the three simulated scenarios.

Chapter 6 compares the results of the optimization across different metrics and identifies the most profitable scenario.

Chapter 7 discusses the results, the precision of the model, and offers an outlook for future work to improve the model further.

Chapter 8 concludes the findings.

2 Theory and Background Knowledge

2.1 Technology description

Bidirectional charging is central to V2G and V2B. Traditional unidirectional chargers allow energy to flow in only one direction, from the grid to the vehicle. Bidirectional chargers enable energy to flow in both directions. Bidirectional charging allows EVs to act as temporary energy storage solutions that can feed electricity back into the grid or home. The EV battery must be charged and discharged with direct current (DC). As the grid uses alternating current (AC), the electricity from the grid must be converted before entering the battery and when exiting the battery to the grid. This can be done in two ways: either by a DC bidirectional charger, where the external charger does the conversion, or an AC bidirectional charger, where the EV itself does the conversion [11].

When the EV is connected to a DC bidirectional charger and is in charging mode, the charger converts AC from the grid to DC. The DC is then fed to the EV's battery via the vehicle's onboard charging system. The vehicle's Battery Management System (BMS) continuously monitors the battery's state of charge, temperature, and health to optimize the charging process and prevent overcharging. The charging process for an AC bidirectional charger is the same, but the conversion happens in the EV. The charging process for both is similar to unidirectional chargers.

The discharging process of an EV using a bidirectional charger is initiated by a signal telling the bidirectional charger to discharge. This request can be triggered by various factors, such as high demand periods on the grid, peak electricity price times, or specific energy needs at home [11]. The EV and the charging station communicate via an established protocol [12], which ensures that both systems align on the amount of power needed and the timing of the discharge. The primary technical action in the discharging process is the conversion of DC from the EV's battery to AC. The conversion happens in an inverter. The inverter adjusts the voltage and frequency of the AC output to match the grid or home system's requirements. The power conversion ensures that the electricity being fed into the grid or home is stable and usable. As the battery discharges, the BMS closely monitors the battery's state of charge, temperature, and overall health. The BMS ensures that the discharge does not lead to battery strain beyond safe operational limits. Various protection mechanisms are active during discharging to prevent issues such as over-discharge. These include setting limits on the minimum state of charge and continuously adjusting the discharge rate based on battery conditions [13].
Once the discharging session is complete, or if the grid no longer requires power, the system safely disconnects the EV from the grid or home system. The charger ensures that all connections are securely deactivated to prevent any electrical hazards.

Every charge and discharge cycle can cause wear on the battery's cells. High temperatures can accelerate chemical reactions in the battery that lead to degradation. Similarly, charging or discharging at very low temperatures can degrade battery performance and lifespan [14]. Studies show that it is the calendar degradation that is the main driver for the battery degradation [14] [15]. It is assumed for simplicity in this thesis that calendar degradation is the only degradation and that other aspects affecting the lifespan of the battery are negligible.

Maintaining grid balance and stability is essential for the efficient functioning of electrical power systems. These elements ensure that the power supply consistently meets the demand without causing fluctuations or outages. Modern grids face challenges due to the implementation of renewable energy sources like wind and solar. Changes in the demand patterns throughout the day amplify the need for balancing. These challenges can lead to periods of energy surplus or deficit, impacting grid stability and increasing operational costs. During peak demand, EVs connected to the grid with a bidirectional charger can discharge part of their stored energy back to the grid. This option to supply electricity back to the grid can reduce the burden on the grid and prevent the need for additional power generation from fossil fuels. At times of low demand and high renewable production, EVs can absorb excess electricity by charging their batteries. This helps in managing the surplus energy and also prepares the fleet for high-demand periods [11].

2.2 Energy community

An energy community enables a collective of individuals living in a community to join forces and invest in sustainable energy. Citizen participation is needed in the energy transition from fossil fuels to renewable energy, acting in communities gives a better utilization of capital.

Energy communities engage in several activities centred around sustainable energy management. The communities generate energy using renewable sources such as PV. The generated energy is used inside the community and the excess is sold or stored. Other than producing energy, an energy community also provides energy efficient services, and can share a distribution network. Many communities also support electric mobility solutions, which include establishing local charging stations for EVs [16].

The two main reasons for an individual to participate in an energy community are the potential for economic savings and a commitment to environmental and social responsibility. An incentive for participating in an energy community is the potential for reduced energy costs. By generating power locally, from renewable sources, energy communities can decrease reliance on national grids and commercial energy suppliers. This local production can lead to significantly lower energy bills for community members. Costs for installing and maintaining systems like PV and battery storage are shared, reducing the financial cost for individuals.
Individuals join energy communities not just for economic benefits but also due to environmental concerns. They want to reduce carbon footprints by using clean energy sources. Such participation helps lessen the effects of climate change and supports sustainability [16].

At the moment legal barriers hinder the possibility of effective power sharing in energy communities in Denmark. Under current legislation for sharing power from one roof, it may only: Share power among homes within the same building as the production facility is established. Or Share power via an internal electricity connection to homes in one neighbouring building, in which case power cannot simultaneously be shared to homes in the building with the production facility. [17].

3 System Description

3.1 Fælledby

This thesis investigates Fælledby as the concrete system. It is located on the outskirts of Copenhagen's municipality. Fælledby is an energy community project underway, consisting of 1726 apartments.

The project's energy strategy revolves around the adoption of photovoltaic (PV) technology, facilitating renewable energy production within the community. Energy storage is a component of the project, with plans to install battery systems in every building, achieving a total storage capacity of 4.32 MWh. This approach seeks to minimize reliance on conventional energy sources and reduce environmental impact.

The buildings are structured in three neighbourhoods each emphasizing sustainable living practices. Substantial underground parking facilities will be constructed at the entrance from the main road (Vejlands Allé) to house a significant portion of resident vehicles [5]. The total parking capacity is 660 cars with 330 chargers, each equipped with two outputs.

Additionally, the Fælledby community will include facilities such as a school, daycare, supermarket, and a hotel, all inside the project's outer ring. Located in the natural surroundings of "Amager Fælled," Fælledby aims to integrate the qualities of a village within a big city.

What makes Fælledby unique is its plan to develop a microgrid that allows electricity to flow from one building to another, thus avoiding the main grid, when possible. This is important as there are many additional costs for operating on the grid, such as taxes, tariffs, and VAT [18], [19], and potentially avoiding these saves a lot of money. This makes Fælledby a potential energy community where inhabitants can share energy. As mentioned in section 2.2, this is currently not legal, but as this thesis analyses a 2035 scenario, it is assumed to be legal by then.

Ultimately, Fælledby seeks to serve as a model for future urban development, not only in the Nordic region but also globally, demonstrating the viability and benefits of sustainable urban practices.

Figure 1: Satellite photo of the Fælledby project plan [20]

3.2 Electricity consumption

The expected yearly consumption of electricity for the energy community has been provided by the Fælledby project and is shown below:

Type	Consumption [MWh/year]
Apartments	4746.5
Hotel	459.1
School and daycare	428.8
Supermarket	120
Total	5754.9

Table 2: Overview consumption in Fælledby

The data provided is a yearly estimate of the consumption in Fælledby, which poses a problem. To do the intended optimization over the individual hours throughout the chosen period, the hourly consumption data is needed. The different components of the hourly consumption, used in the model, rely on assumptions that are explained in the following sections.

The hourly electricity consumption for apartments in Fælledby relies on data sourced from "Energi Data Service" [21], they provide a dataset with the electricity consumption of all the municipalities in Denmark for a given year, starting from 2021 onward. 2023 was selected as it is the most recent complete year available. Ideally, the consumption data from 2020 would have been preferable to synchronize with the PV production and price data from the same year. However, this dataset is not available for the specific municipality in question. It is assumed to be acceptable to choose a different year for the consumption as long as the weekdays align accordingly with the PV and price year. This adjustment involves shifting the 2023 data forward by four days to ensure that the weekdays align properly with the 2020 datasets. This alignment is crucial for maintaining consistency across the different data sets and ensuring the accuracy of the energy consumption.

For this analysis, the dataset for the municipality of Copenhagen is utilized, because of the Fælledby's location within this municipality. The dataset is divided into three sectors: industry, public and private. Given the scope of this thesis, attention is directed solely towards the private sector. By implementing these constraints on the dataset the hourly private consumption of electricity in the municipality of Copenhagen is found. It is assumed that the load profile of Fælledby apartments will match that of the municipality they are within. Summer and winter variations in consumption of the apartments already exist in the dataset retrieved from "Energi Data Service" [21].

The Fælledby project anticipates an annual electricity consumption of 2.75 MWh per apartment. The hourly electricity consumption of Copenhagen is scaled accordingly so the sum of consumption for a year matches the 2.75 MWh/year estimate from the Fælledby project.
With 1726 apartments in Fælledby, the hourly electricity consumption for each apartment is multiplied by this figure, providing the total electricity consumption for all apartments within the energy community. Below is seen the average consumption profile on weekdays for winter and summer.

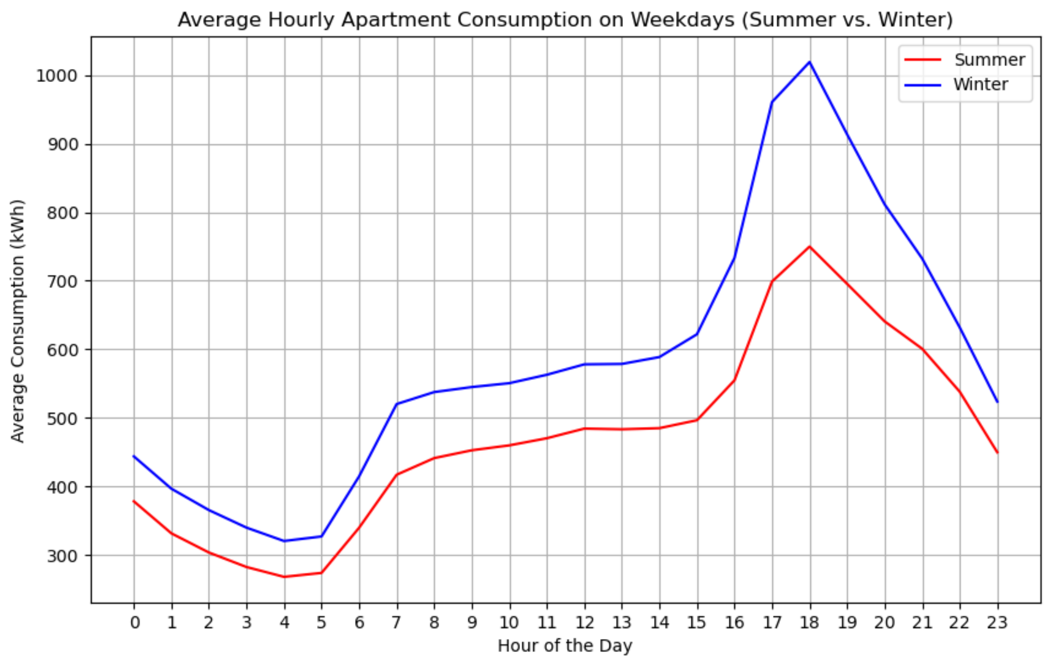

Figure 2: Average apartment electricity consumption on weekdays for summer and Winter

The hourly consumption profile of the hotel is assumed to be the same as that for the apartments. The assumption builds on a study of hotels in Marrakech [22] where the hourly consumption in the winter looks like that of the apartments in the municipal in Copenhagen. The hotel consumption is added by scaling the consumption for the apartments to consume 459.1 MWh/year more.

The hourly consumption profile of the school and daycare is synthesised by looking at the Power Demand profiles of schools in the study "Energy Consumption In Non-Domestic Buildings: A Review of Schools" [23]. It is assumed that it is the same profile for every school day of the week and that the lowest consumption of the day is the constant consumption on the weekends. School summer vacation is treated similarly to weekends, with low consistent usage throughout the period. Summer and winter variation in the school and daycare consumption is assumed for simplicity to be non existing. The school and daycare consumption for the day is seen below.

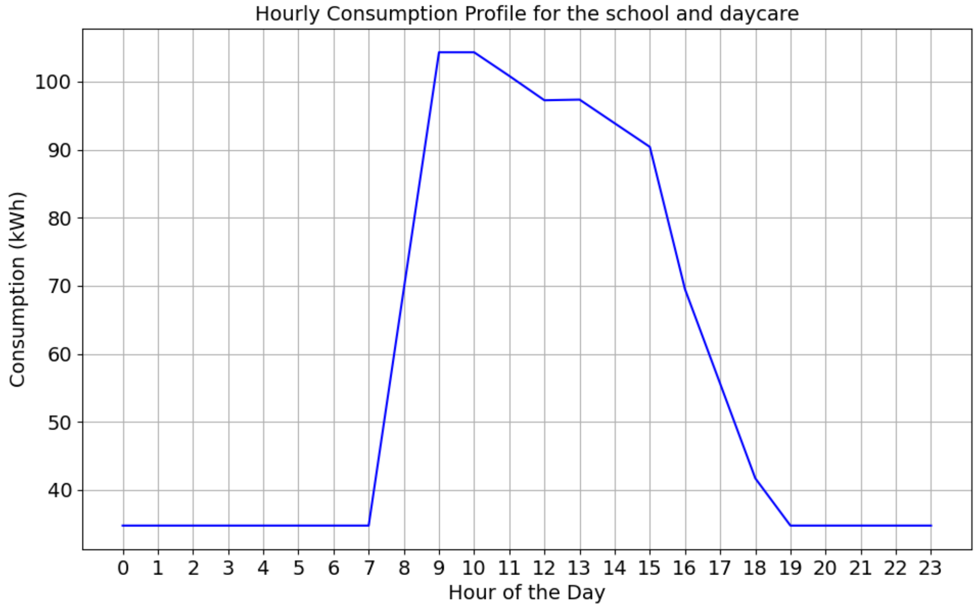

Figure 3: Electricity consumption by Fælledby school and daycare

The hourly consumption profile for the supermarket is synthesized from a study titled "Energy Sustainability of Food Stores and Supermarkets through the Installation of PV Integrated Plants" [24]. The profile is duplicated from the study and scaled to match the yearly estimate for the Fælledby consumption for the supermarket. Summer and winter variation in the supermarket consumption is assumed for simplicity to be nonexistent. The consumption of the supermarket is seen below

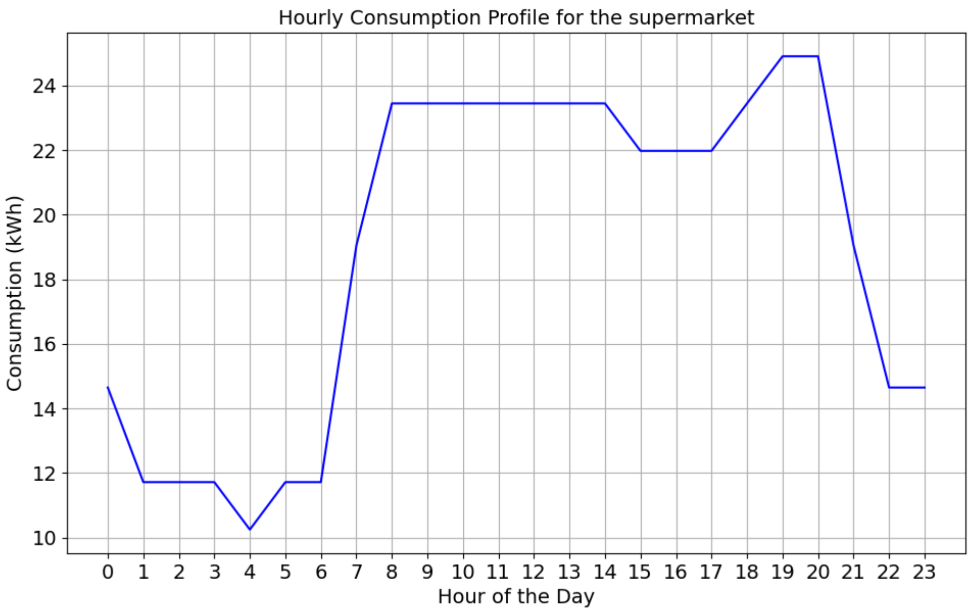

Figure 4: Electricity consumption by Fælledby Supermarket

The consumption from the different components is combined into one dataset and fed into the simulation model. The load profiles for the combined consumption for the weekdays and the weekends for Fælledby are shown below:

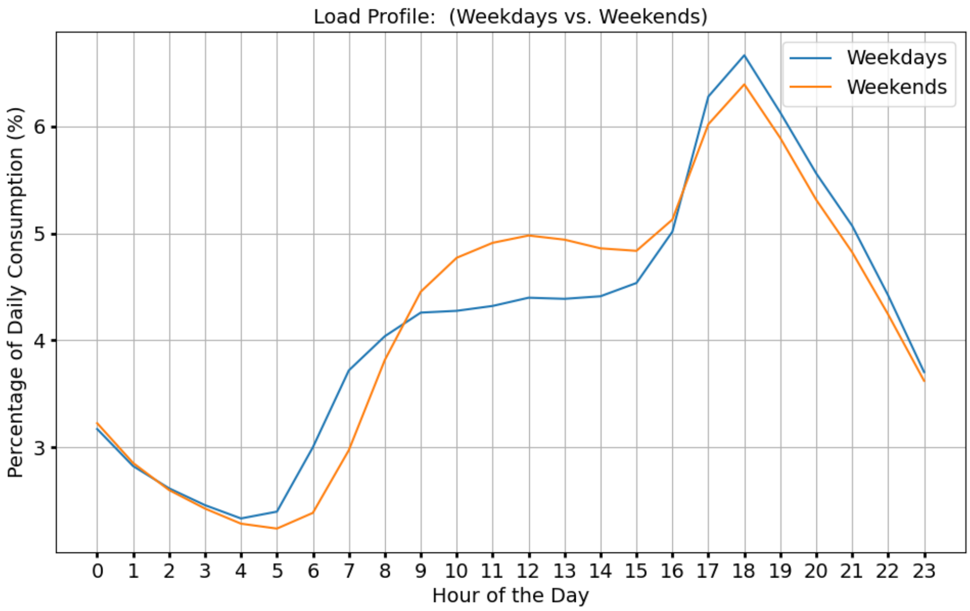

Figure 5: Load profile for the weekday and weekend for Fælledby consumption

The load profile for the weekdays and the weekends depicts an expected difference between the weekend and weekday consumption. The hourly consumption constructed in this section only represents the consumption by the buildings in Fælledby and not the consumption of the EVs.

3.3 PV

Fælledby comprises 23 building areas, 22 of which are equipped with PV on their roofs. The PV systems exhibit five distinct combinations of slope and orientation, contributing to a total capacity of 4,771 kWp. The PV technology used is crystalline silicon with a 98% effective inverter. Below, Table 3 provides an overview of the slope and orientation combinations alongside their respective capacities:

Slope [°]	Orientation	Capacity [kWp]
15	East	1036.8
30	East	929.2
30	West	922.4
30	North	941.3
30	South	941.3

Table 3: Overview PV

The data presented in Table 3 is sourced directly from the Fælledby project. Notably, the distribution of capacity among the different combinations is relatively equal. Having these different combinations provides a more evenly spread PV production profile throughout the day, as opposed to relying solely on south-facing orientations. Two of the five combinations of PV, with relatively equal shares, are eastern-oriented. It is expected that the production earlier in the day will be higher than later in the day. This is due to the positioning of the panels to capture the morning sunlight, leading to an earlier peak in energy generation.

The modeling of the PV production in Fælledby builds on data from the "Photovoltaic Geographical Information System" [25]. They provide data from the year 2005 to 2020. The year 2020 was used because it is the most recent data available. The slope and orientation, provided by the Fælledby project, were entered into the calculation system together with an efficiency of 98% and the type of PV panels. The output is five different PV production profiles for the five different combinations of slopes and orientation, as seen in Table 3. The profiles were scaled according to the capacity of the combination in Fælledby and put together in one data frame to be used in the simulation. The data frame consists of the electricity produced every hour by the PV panels installed on the roofs of the buildings in Fælledby. Below is the PV production for a sunny day in July and for a sunny day in January.

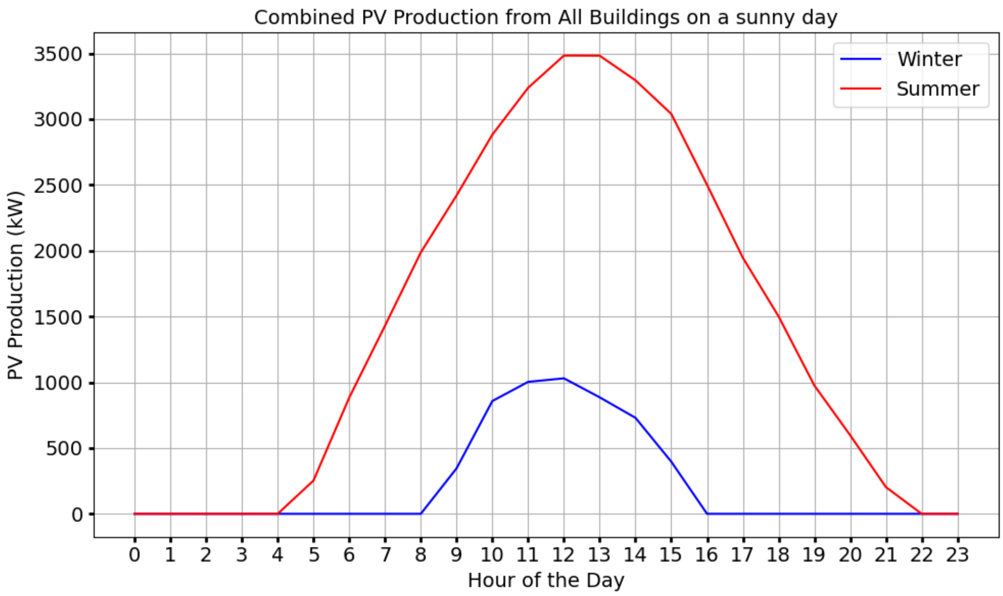

Figure 6: PV production on a sunny day for summer and winter

As expected the PV production on a sunny summer day is larger and higher than on a sunny winter day.

3.4 Electricity price

The electricity price used in the simulation is constructed from the DK2 electricity spot price collected from "Energi Data Service" [26]. They provide data from the year 1999 until the current date. The year 2020 was chosen to match the year of the PV production; this is done because there is a correlation between the electricity spot price and the PV production [27]. The electricity spot price is the base electricity cost and is assumed to be the sell price. On top of the spot price, consumers have to pay tax, tariffs, and VAT. These components are retrieved from "Energinet." The tariffs are divided into two: the transmission system operation (TSO) tariff and the distribution system operation (DSO) tariff. The components are retrieved from the year 2023 and represent the newest taxes, tariffs, and VAT. The tax is 95.13 Øre/kWh [18], the TSO tariff is 12.2 Øre/kWh [19], and the VAT is 25%. The VAT is applied after all the other components. The DSO tariff has different values for different periods. The winter tariff is applied between October and March, and the summer tariff is applied from April to September. The DSO tariff changes throughout the day. The periods and the values are shown below in Table 4 and Table 5.

	00-06	**06-17**	**17-21**	**21-24**
Winter	Low period	High period	Peak period	High Period
Summer	Low period	High period	Peak period	High Period

Table 4: DSO periods [18]

Period	**Winter**	**Summer**	
Low period	15.19	15.19	Øre/kWh
High period	45.56	22.77	Øre/kWh
Peak period	136.68	59.23	Øre/kWh

Table 5: DSO tariff[18]

All components added to the DK2 electricity spot price determine the final price paid by the consumer. The selling price is assumed to be equivalent to the DK2 spot price. The buying and selling prices utilized in the model are shown for the average day in summer and the average day in winter in the Figure 7 below:

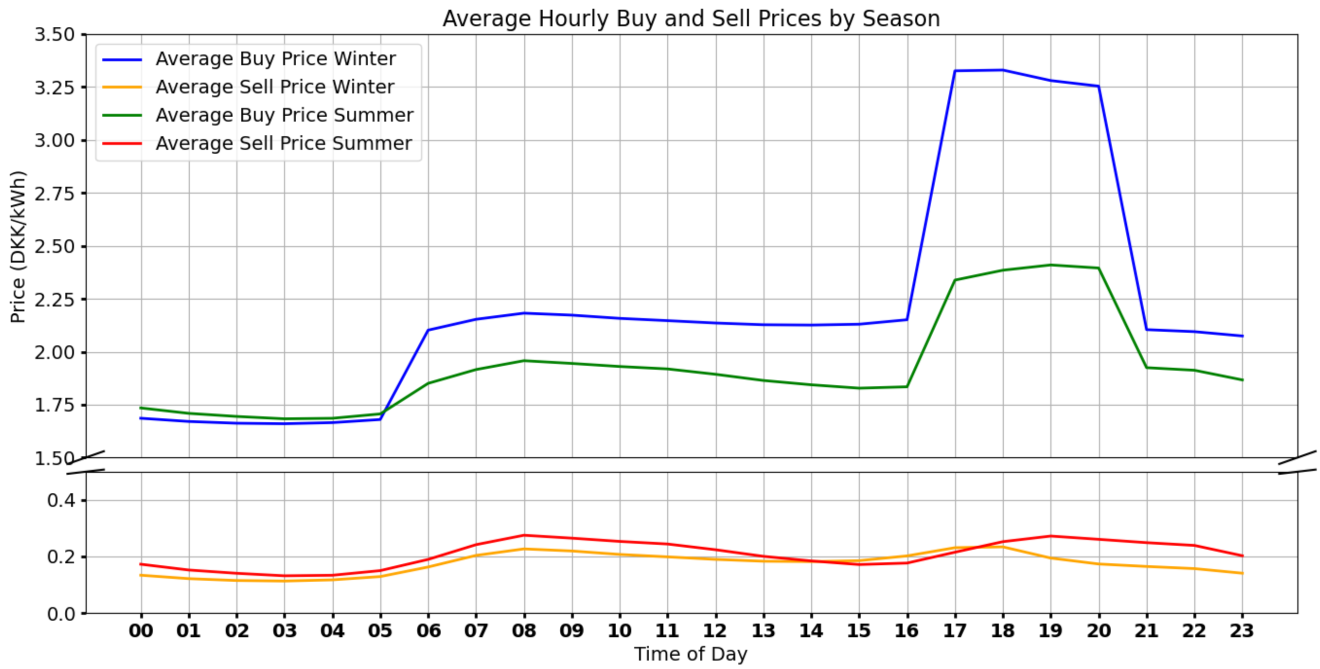

Figure 7: Average buy and sell price for winter and summer

The average prices for the two seasons show how the DSO tariffs affect the buying price both in summer and winter, but significantly more in the winter.

3.5 EVs and chargers

The Fælledby project expects a total of 660 cars within its community by its finished construction. However, it does not specifically forecast the proportion of these cars that will be EVs. To address this gap, an estimation method is proposed based on broader trends in Copenhagen and assumptions. The method for estimating the number of EVs in Fælledby builds on the assumption that the percentage of cars that are EVs in the municipality of Copenhagen in 2035 is the same in Fælledby.

There are 146,222 cars in the municipality of Copenhagen today [7], and there were 653,648 residents in the Copenhagen municipality as of Jan 1, 2023 [28]. This gives a car per capita rate of 0.224, which is assumed to remain the same in 2035. According to projections, the population of Copenhagen Municipality is expected to grow by approximately 5,500 residents annually [28], reaching a total of 718,648 by 2035. Applying the 2023 car per capita rate to the 2035 population estimate yields a total of 161,206 cars in 2035. It is estimated that there will be 140,110 EVs in the municipality of Copenhagen in 2035 by "Dansk E-Mobilitet" [7]. Dividing the number of projected EVs by the total projected number of cars gives an EV penetration rate of 87.9% in the municipality of Copenhagen in 2035. The projection of EVs comes with uncertainties, and other studies may land on different estimates for the 2035 EV penetration rate. Utilizing the derived EV penetration rate from Copenhagen, the estimated number of EVs in Fælledby by 2035 can be calculated. Applying the 87.9% rate to the 660 vehicles expected in Fælledby results in 574 EVs in Fælledby by 2035.

Bidirectional charging is an upcoming technology, which EV manufacturers are aware of. Tesla is one of the largest manufacturers, and they plan on adopting the technology by 2025 [29]. Volkswagen, Nissan, Hyundai, KIA, FORD, and MG already have it incorporated in some models [30]. In this thesis, it is assumed the trend continues, and by 2035 all of the EVs in Fælledby are equipped with the technology.

The current plan includes the installation of 330 chargers, each equipped with two standard outlets, providing a capacity of 11 kW per outlet. While the specific model of EV chargers has not been finalized by the project management, it is assumed that each charger can discharge at 11 kW as well. 300 of these chargers will be placed in the main underground parking, and the rest in smaller parking areas in Fælledby.

3.6 Model of driving patterns

The main challenge in utilizing EV batteries for buildings is that their primary purpose is transportation. The availability of EVs is variable, and their energy expenditure during driving reduces the amount of energy available for contribution to a building. Compared to stationary batteries, which offer constant availability and full energy capacity, EVs provide less consistent and contributable energy. Additionally, there is a mismatch between when cars are used and when PV is produced. Cars are often used during the day when PV production is peaking, and therefore potential overproduction cannot be captured by the EV. Assuming not all cars are gone at the same time, some of this mismatch might be mitigated by an energy community, allowing the available EVs to charge. To figure out how much can be mitigated, it is vital to know the driving patterns of the energy community's EV fleet. Therefore, modelling the driving patterns is an important part of this thesis to determine the economic value provided by V2B.

3.6.1 Model purpose

The model's objective is to synthesize the driving patterns of Fælledby's EV fleet by modeling the hourly availability and travel distance. These two parameters are vital to the optimization model as the EVs can only charge or discharge when they are available, and the distance traveled depletes the batteries. The model does this by replicating real driving data. By replicating the input data, the input data can be filtered such that it is representative of the Fælledby inhabitants. This was done through geographic, demographic, and seasonal filters. Finally, the model simulates the driving patterns of all Fælledby's EVs during a week of summer and a week of winter.

3.6.2 Model data, filtering, and assumptions

The driving habits of the EVs in Fælledby were based on data from DTU's "Transportvaneundersøgelse" (TU). TU is one of the most comprehensive transport surveys in Denmark with over 400,000 interviews [31]. The survey has entries from all over Denmark and has collected data since 1975, with the newest dataset including data from 2006 and onward with around 11,000 new entries every year. The large number of data points, combined with a session weight for every response, results in a robust model and allows data filtering without compromising the accuracy of the predictions.

The first filtering was a geographical filter; as Fælledby is located in Copenhagen municipality, only entries from there were used. Secondly, only new data was used as COVID-19 resulted in quarantine and less travelling in general; therefore, only data from 2022 and forward were used. Not all people have regular access to a car, and therefore the interviewees without a car in their household were filtered out. Additionally, a filter was applied such that all interviewees had a driver's license; this was done to only get data from those who actually drove. Lastly, to ensure the interviewee is a primary car user, an age filter was applied to exclude individuals under 25. This was to prevent the misclassification of young adults with a driver's license, who still live at home, from being incorrectly identified as the primary car user. The driving habits were modeled both during summer and winter, and to achieve this, a seasonal filter was applied. For the winter data, only December, January, and February were used, and for the summer data, June, July, and August were used.

One shortcoming of the TU survey is that it records people's daily transport activities rather than specifically their daily car usage. This means that all types of trips, such as those by metro, bus, and walking, are logged. The issue arises when examining car trips because assuming the TU data is representative of overall car usage implies a 1:1 ratio of people with driver's licenses to cars, with each car always driven by the same individual. This is an incorrect assumption, as there are far more people with driver's licenses than there are cars.

To overcome this, some assumptions about car users had to be made. The first assumption was that all households have exactly one car. The second assumption was that every car had exactly two drivers/primary users. Lastly, assuming that the TU data was representative of both drivers allowed the simulation of all the trips made by the two drivers, and thereby all the possible car trips. These assumptions are fairly close to the filtered data from TU, which averages 1.78 driver's licenses and 1.17 cars per household.

With these filters and assumptions, the dataset contained only the transportation habits of primary car users. By assuming that each car has exactly two primary users with identical transportation habits, it was possible to model the combined distribution of daily trips of two primary users. Then, applying the probability of these trips being made by car, the distribution of daily car trips was derived.

3.6.3 Daily trips

The first part of the model involved extracting the distribution of the daily number of trips for each day of the week by a single person. This was done by counting the trip amounts for the given day and dividing by the total number of trips that day:

$$p_{trip}(d)(n) = \frac{trip_{count}(d)(n)}{trip_{count}(d)}, \quad \text{for } d = 1, 2, 3, \ldots, 7, \quad \text{for } n = 0, 1, 2, \ldots, 5 \tag{1}$$

Here d is the day of the week and n is the amount of daily trips ranging from 0 to 5 as five trips was the maximum recorded amount. This resulted in the following distributions:

Number of trips	0	1	2	3	4	5
Monday	0.10	0.30	0.44	0.14	0.02	—
Tuesday	0.08	0.32	0.42	0.12	0.04	0.02
Wednesday	0.11	0.27	0.41	0.12	0.04	0.04
Thursday	0.12	0.28	0.44	0.05	0.09	0.01
Friday	0.08	0.22	0.35	0.20	0.13	0.02
Saturday	0.28	0.31	0.21	0.10	0.02	0.08
Sunday	0.16	0.34	0.30	0.17	0.03	—

Table 6: Distribution of amount of daily trips

This shows the respondents are most likely to have one or two daily trips.
Based on the assumption that there are exactly two drivers represented by the TU data, the cumulative distribution of the daily number of trips by two drivers was computed. This was done by convolving the distributions in Table 6. This was done for each row using Equation 2 below.

$$q_n = \sum_{m=0}^{5} p_m \cdot p_{n-m}, \quad \text{for } n = 0, 1, 2, \ldots, 10 \tag{2}$$

Here q_n is the probability of trip amount n, and p are the probabilities from Table 6, which are zero when $n - m$ is less than zero or larger than five. Doing this for every day of the week resulted in the new distribution of combined daily trips by two people, seen below in Figure 8:

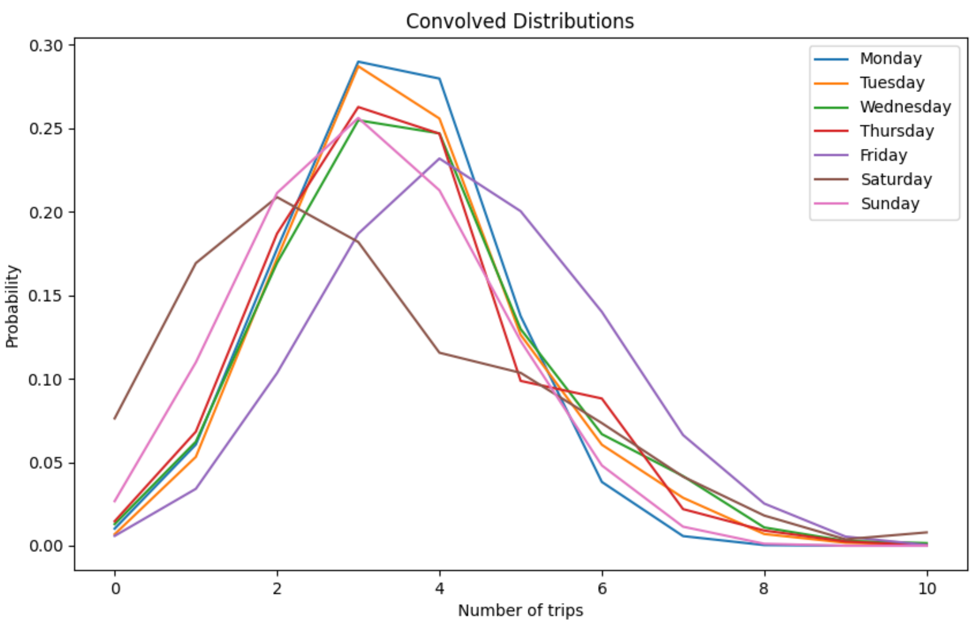

Figure 8: Convolved distribution of trips

From Figure 8, the most common occurrence is a combined trip total of 3-4 for two people. Friday and Saturday stand out as Saturday has visibly fewer trips than the other days of the week, and Friday has more. The distribution of daily trips does not indicate how much a car is used, as these could be any kind of trip—walking, biking, public transport, etc. Therefore, the probability of a trip being done by car is required. This was done for every day of the week in the same way the number of trips was found.

$$p_{car}(d) = \frac{n_{cartrips}(d)}{n_{trips}(d)}, \quad \text{for } d = 1, 2, 3, \ldots, 7 \tag{3}$$

The probabilities of a trip being made by car were:

Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
0.34	0.39	0.42	0.32	0.32	0.45	0.45

Table 7: Probability of a trip being by car

Combining the distribution of daily trips with the probability of a trip being made by car allows for the modeling of daily car trips for a larger fleet using a Monte Carlo simulation. However, it does not provide information about the length, start, and end times of these trips. Therefore, the next step of the model was to analyze the TU data for the actual trip patterns.

3.6.4 Trip data

The optimization model needs to know if an EV is available and how long it has driven to model the SOC of the battery. Therefore, the synthetic driving data needed to include trip leaving time, duration, and distance driven.

TU has created five general categories for trip purposes: 'Workplace,' 'Errand,' 'Leisure,' 'Educational,' and 'Business.' This model will utilize the first three since very few car trips are for education, and business driving is excluded as it is difficult to determine whether or not these trips are done with private vehicles.

From TU, the distribution of these three categories throughout the week is extracted using the equation below (Equation 4):

$$\begin{aligned}
p_{work}(d) &= \frac{n_{work}(d)}{n_{work}(d) + n_{Errand}(d) + n_{Leisure}(d)}, \quad \text{for } d = 1, 2, 3, \ldots, 7 \\
p_{Errand}(d) &= \frac{n_{Errand}(d)}{n_{work}(d) + n_{Errand}(d) + n_{Leisure}(d)}, \quad \text{for } d = 1, 2, 3, \ldots, 7 \\
p_{Leisure}(d) &= \frac{n_{Leisure}(d)}{n_{work}(d) + n_{Errand}(d) + n_{Leisure}(d)}, \quad \text{for } d = 1, 2, 3, \ldots, 7
\end{aligned} \tag{4}$$

The results of these are seen below in Table 8.

Day	Work	Errand	Leisure
Monday	0.31	0.37	0.32
Tuesday	0.39	0.31	0.30
Wednesday	0.49	0.25	0.26
Thursday	0.39	0.42	0.19
Friday	0.47	0.21	0.32
Saturday	0.02	0.32	0.66
Sunday	0.00	0.31	0.69

Table 8: Distribution of Daily Trips by Purpose

These results seem intuitive as almost no trips are for work during the weekend, and most trips during the weekend are for leisure. However, the purpose of this model is to determine the availability and travel length of the EV fleet. Therefore, data about the three trip types needed to be extracted for each of these categories. The data to be extracted was trip distance, trip start time, and trip duration. This data was extracted as a dataset so the model could replicate these for the synthetic Fælledby data.

To account for different types of distributions in the datasets, the resampling was done using the inverse empirical distribution function (EDF). The inverse EDF works by inputting a dataset X to be replicated and a random number p (from a uniform distribution $U(0,1)$). The output is then a synthetic data point based on the distribution in X. In total, nine inverse EDFs were used to simulate the duration, start time, and length for the three categories: work, errand, and leisure.

The EDF assigns a cumulative probability to each point in a dataset based on its rank within the sorted data. For a dataset $X = \{x_1, x_2, ..., x_n\}$ the EDF is defined as follows:

$$F_n(x) = \frac{1}{n}\sum_{i=1}^{n} I(x_{(i)} \leq x) \tag{5}$$

I is the indicator that returns 1 if $x_{(i)} \leq x$ and 0 otherwise. The EDF was applied to the dataset by first sorting the dataset X:

$$\begin{gathered} X_{sorted} = \{x_{(1)}, x_{(2)}, ..., x_{(n)}\} \\ \text{where } x_{(1)} \leq x_{(2)} \leq ... \leq x_{(n)} \end{gathered} \tag{6}$$

The EDF can then be applied to the sorted dataset like so:

$$F_n(x_{(i)}) = \frac{i}{n} \tag{7}$$

The inverse EDF works $F_n^{-1}(p)$ works by mapping a probability p (from a uniform distribution $U(0,1)$) to a corresponding value in the original dataset X. However, due to the discrete nature of the dataset, the probability of an exact match between p and F_n is low. Therefore, linear interpolation is used between the two closest values of F_n corresponding to the positions in X_{sorted}.

The inverse EDF looks like this:

$$F_n^{-1}(p) = x_{(k)} + \frac{(x_{(k+1)} - x_{(k)}) \times (p - F_n(x_{(k)}))}{F_n(x_{(k+1)}) - F_n(x_{(k)})} \tag{8}$$

here $x_{(k)}$ and $x_{(k+1)}$ are the closest data points in X_{sorted} such that $F_n(x_{(k)}) \leq p \leq F_n(x_{(k+1)})$.
The inverse EDF is versatile as it mimics the input data. In this model different seasons and different trip purposes are modelled, and by changing the input data to match this, the EDF generates data accordingly.

The synthetic data generated for the errand category is seen below:

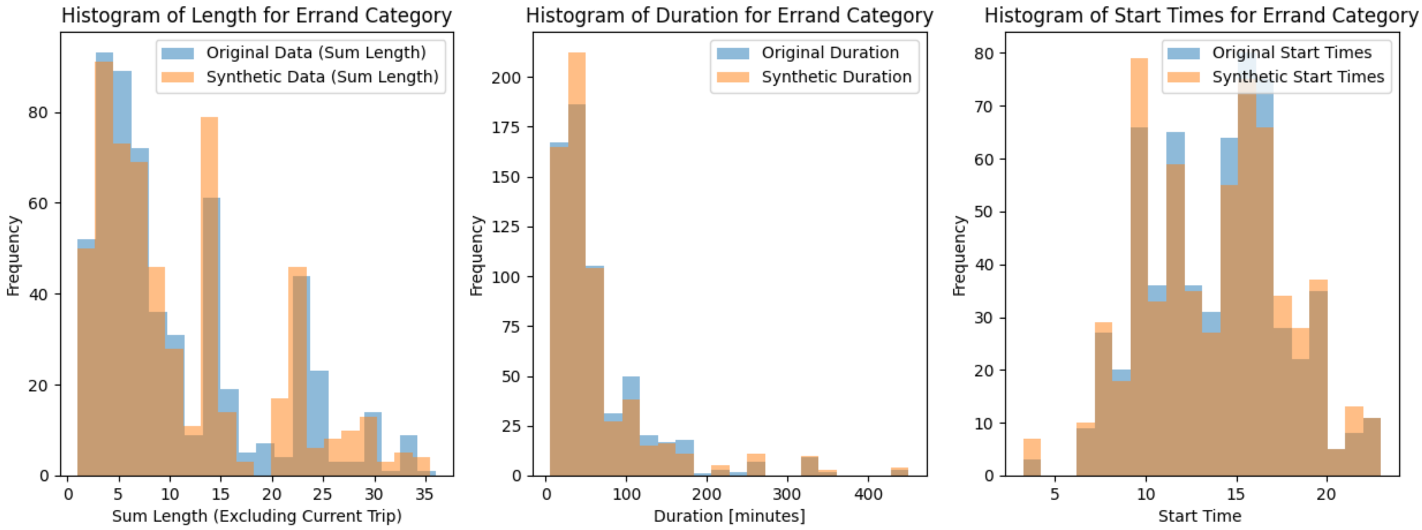

Figure 9: Original and synthetic data for the Errand category

As seen from the three figures in Figure 9, the inverse EDF works well to replicate the original data. With this, it is then possible to generate entirely synthetic data for Fælledby's fleet of cars by first simulating a number of trips for a given car, then choosing one of the three categories based on the probabilities in Table 6. Lastly, the three relevant inverse EDFs were used to simulate the statistics for the given trip.

To generate the synthetic driving data, three parameters were chosen: a start date, a duration of days, and a number of cars. For each day, a number of trips are chosen based on the day of the week and the convolved number of trips distribution. Then each of these trips are determined as a car trip or not, this is based on the probability for the given day. The trips that are deemed to be made by car are then given a purpose: work, errand, or leisure. The inverse EDF for that purpose is then applied to generate a drive distance, start time, and duration. This is done once per day for every car for the duration chosen. Applying this to the entire fleet of Fælledby with summer and winter data results in an average of 0.81 trips per day per car and an average daily driving distance of 37.9 kilometers during winter. During summer it averages 0.84 trips per day per car and 35.8 kilometers on average during summer. This means that people drive slightly longer trips during the winter but also less often. Vital to the model is the number of cars available to do V2B in Fælledby, and below in Figure 10, the hourly number of cars home during a day of winter is shown:

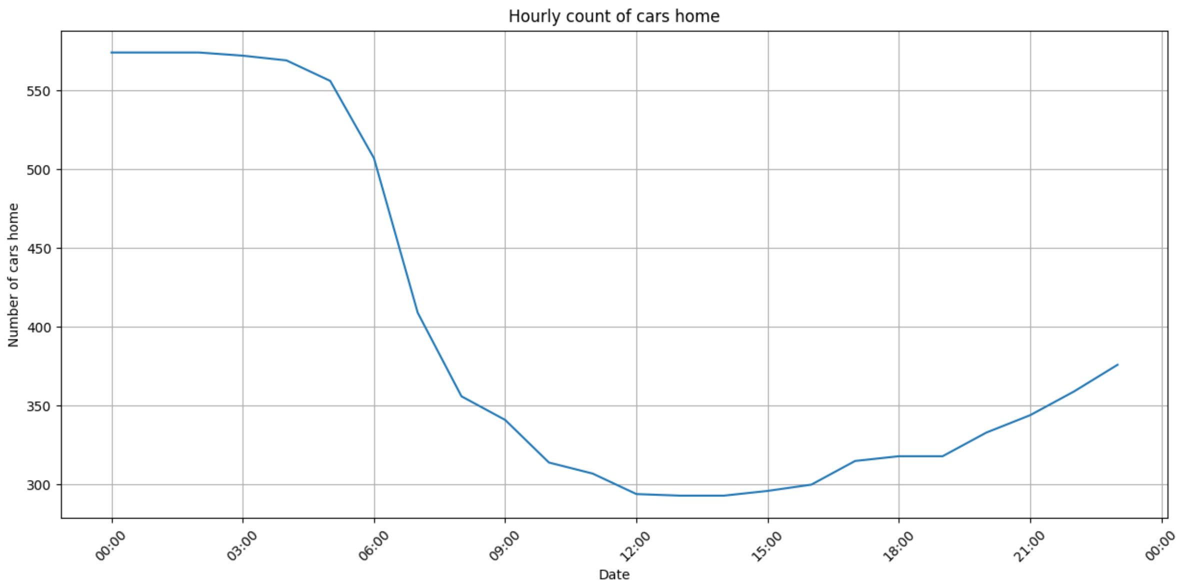

Figure 10: Hourly number of cars home during an average day

This shows that during the night every car is home, and during the day, roughly half of the cars are gone. The reason why not more cars are gone at the same time, even though the average daily trips are 0.81, is because the cars have different departure times and durations. As a result, around half the fleet is home at all times. At 23:00 there are still 200 cars that are not home. The reason for this is the simulation stacks trip on top of each other. So if there are two trips simulated with a long duration, those are added on top of each other. This results in the cars being away for longer than they most likely would. At 00:00 all cars are assumed home ready for new simulation of trips.

3.6.5 Validating the synthetic data

To validate the model, the actual daily driving distance in Copenhagen is compared to the distance predicted by the model. From [7], the average daily driven distance in Copenhagen is 35 km. This closely resembles the average distance during summer and is slightly smaller than the average during winter. The model is based on a number of assumptions, and therefore this deviation from the actual daily driving distance is deemed acceptable.

4 Optimization Model

This section details the optimization process and the assumptions behind it. The optimization is crucial for accurately simulating the three scenarios and evaluating their effectiveness and potential value for Fælledby. The optimization of the three scenarios was conducted in Python with Gurobi [32] as the selected optimization solver. Gurobi was chosen for this project based on recommendations from coworkers who have had positive experiences with its performance.

The goal of the optimization was to find the best possible charge and discharge patterns for every EV in Fælledby. The basis of this was that the cost of the sum of bought and sold electricity should be the lowest possible for the duration of the optimization. The objective is defined below in Equation 9:

$$\min \left(\sum_{t=1}^{168} E_{bought(t)} \times p_{buy(t)} - E_{sold(t)} \times p_{sell(t)} \right) \tag{9}$$

Here, E represents the amount of electricity bought and sold for a given hour, and p represents the buy and sell price for the hour. Before the optimization could begin, different parameters and assumptions had to be made and they are explained in detail in section 4.1.

4.1 Constants and assumptions

This section details the assumptions regarding the EVs and system efficiencies. These assumptions are based on current technology and are scaled, when reasonable, to forecast conditions in 2035. Below is an overview of the assumptions made for the model see the following text for references and in depth explanations.

Overview of Assumptions	Values	Central to the assumption
Charge rate	11kW	Given by Fælledby project
Discharge rate	11kW	Given by Fælledby project
EV Charge and discharge efficiency	90% for both	Based on current chargers peak efficiency
Stationary Battery Charge and discharge efficiency	95% round trip efficiency	Given by Fælledby project
Driving efficiency	20 kWh/100km	Retrieved from studies [33]
EV battery capacity	75 kWh mean, 10 kWh standard deviation	Based on current projection for 2030 assuming the increase will keep going
Maximum SOC while charging EV	80 % SOC for charging	This is assumed for battery health
Max and min SOC for stationary battery	Max SOC 95% Min Soc 10%	Given by Fælledby project
Depth of discharge EV	20 kWh	Assuming that the owner always should be able to drive 100km for emergencies.
Initial State of Energy (SOE) EV	20 kWh	Sat low to not add too much initial energy to the system.
Initial State of Charge stationary battery	20%	Sat low to not add too much initial energy to the system.
SOE in EV before a trip	Energy needed for the trip + 20 kWh	Assuming perfect knowledge about the trips and a buffer of 20 kWh
Maximum Power in the system	3700 kW	Based on the amount of transformers and the amps for them.
EV availability		The EVs are pluged in after the trips, for the day, are done.
Energy community		Energy sharing is possible.
Charging in the community		All charging of the EVs are done in Fælledby. No external energy eg. from work
Perfect knowledge		This model assumes perfect knowledge for the simulated period.

Table 9: Overview of assumptions in the Model

An in depth explanation of the chosen values and assumptions seen in Table 9 are described below.

Charge and discharge rate

The charge and discharge rate of the EVs is a vital part of the system as it determines if the available EVs can capture the production of PV. The data on Fælledby provided by COWI estimates that chargers are capable of 11 kW charging and the discharge rate is assumed to be the same.

Charge and discharge efficiency

The efficiency of charging and discharging accounts for many losses in the energy community setting. EVs available during peak PV production might have to charge those who were not available, thereby causing the charge and discharge loss to occur multiple times. Quasar [34] and Emporia [35] target

97% and 95% peak efficiency. In the simulation, a flat discharge and charge efficiency is used and is therefore chosen a bit lower at 90%.

Driving efficiency

The EVs expend energy driving, and to figure out how much, a drive efficiency is required. The average of a long list of models is 18.8 kWh/100km according to the Electric Vehicle Database [33]. Since this is the average over a long list of models with one of each, it is not representative of the EV fleet in Denmark. A bit more conservative efficiency of 20 kWh/100km is therefore used in this model.

EV battery capacity

The EV battery capacity determines how much energy can be stored in the energy community and is therefore another vital factor. According to Mackenzie analyst Max Reid [36], the average capacity was 51 kWh in 2020, and by 2030 it will be 69 kWh. Assuming this trend will continue linearly, the capacity in 2035 will be 78 kWh. The assumption of a linear increase is a bit bold, and therefore the average capacity is assumed to be 75 kWh in 2035. Furthermore, to simulate different battery capacities, a standard deviation of 10 kWh is used.

Maximum Soc and minimum SOE

It is assumed earlier in this thesis that cycle degradation is negligible and that the only degradation is calendar degradation[14] [15]. To further ensure that cycle degradation doesn't play a role in the scenario, boundaries for the depth of discharge and the height of charge are set when doing V2B. The lower boundary for discharging during V2B is set to 20 kWh. The upper boundary for charging during V2B is set to 80% SOC. The upper boundary was chosen as studies show that this is a good maximum level of the SOC that maintains battery health while still utilizing the battery for its purpose [37]. The rationale for setting a minimum State of Energy (SOE) at 20 kWh is to ensure that EVs maintain a baseline range of at least 100 km. This precaution accounts for unexpected circumstances that might necessitate travel and ensures the EV has enough charge to cover that distance.

Initial state of energy

The Initial SOE is an important metric in this model, as only one week is modelled at a time and therefore the initial SOE has a big impact on the overall outcome. An overall initial SOE that is too high could result in the system starting with "free" energy, which could inflate the results. Therefore, a relatively low initial SOE of 20 kWh was chosen. This is also the Minimum SOE and therefore there is no "free" energy in the system. A better and more precise way to model the initial SOE would be to use the Hipolito Model [38]. The model approximates the steady-state distribution of state of charge (SOC) levels for EVs at the beginning of the day. However, this was not based on EVs capable of bidirectional charging. In the optimization model, the end-of-the-week distribution of SOE approximates the minimum SOE chosen of 20 kWh. It does this as the more energy deployed from the EV batteries to cover consumption results in less bought electricity and a lower price. In the end the optimization model does not take the day after the simulation period into consideration, and just deploys as much energy as possible. Therefore, basing the initial SOE on the Hipolito model would create an unfair advantage. Becuase the end of the optimization the EVs in the V2B system approaches a SOE of 20 kWh which is less than the steady state predicted by the Hipolito model.

Maximum current and power

Fælledby has three different zones and COWI estimates between two and four transformer stations in each zone connected to the grid. Each transformer station is capable of 600 A. The average of three transformer stations is assumed, totaling nine transformer stations in Fælledby with a total capacity of 5400 A. The model is based on power and energy, and therefore a maximum power is required too. A three-phased system of 400 volts is assumed:

$$5400A \times 400V \times \sqrt{3} = 3741kW \tag{10}$$

Assuming there are some small losses in this conversion, the maximum system power is set to 3700 kW.

EV availability

EV availability is an important parameter as it determines if the EVs can charge or discharge to the energy community. The more EVs available, the more advantageous. It is obvious that when the EVs are gone they are not available, however, a question arises when the EVs are home as they need to be plugged in to be available. In this model, it is assumed that when the EV is done with all their trips for the day, the EV is plugged in. The reason for this is that if more than one trip is done during the day, it might be unlikely that the car is plugged in if the EV owner knows that the next trip will just be a short one to the supermarket. The second part of the assumption is that everyone plugs in when they are done traveling for the day, as there hopefully will be a consensus within the community that it is to the mutual benefit of everyone.

Energy community

The benefit of this model comes from the possibility of energy sharing within the community. Fælledby is planning on establishing an energy community, however, with the current legislation, this is not currently legal [17]. The assumption is, that by 2035 energy communities will become feasible legally.

Charging in the community

Charging requires a substantial amount of energy, and therefore has the potential to be expensive. To make sure there is no "free energy" in the model, potentially creating an overestimation of value, it is assumed that all charging is done in Fælledby. Additionally, long trips that require more energy than what is available in the battery, assumes the EV returns with a SOC of zero. Lastly, this model only relies on the inhabitants' EVs and outside EVs of the people that work at either the school or hotel are not a part of this model.

Perfect knowledge

This model operates under perfect knowledge as PV production, electricity prices, electricity consumption, and driving patterns are all known beforehand. As the model runs for a week, it could be argued that it is somewhat reasonable for PV, electricity prices, and consumption as prediction models forecast those fairly well[39]. The driving patterns are another case as people most likely will not register all of their drives a week in advance. However, people do have patterns like going to work and coming back at roughly the same time, which could be predicted. Given an easy enough way to register, it might also be reasonable to assume that people going on a long drive will register in advance to make sure their EV has the correct SOC for their trip. Unregistered trips under 100 km will always be drivable, as the V2B does not allow the EV to drain beneath 20 kWh.

4.2 V2B optimization Model decision variables and constraints

As per the introduction in section 4, the objective of the model was to achieve the lowest electricity cost over the simulated period. The model had data for every hour of the simulation duration and thereby chose the optimal solution through a range of decision variables. In total, the V2B model had three decision variables which were:

- Hourly power bought
- Hourly power Sold
- Hourly power EVs

These three variables are vital as they are crucial for maintaining the power balance in the system. The power balance in the system must be maintained precisely, and therefore these decision variables are continuous values, meaning they can take any value within a given range. The relation of these is seen in the power balance equation 11 below:

$$P_{demand(t)} + \sum_{i=1}^{574} P_{EV(t)(i)} = P_{bought(t)} - P_{sold(t)} + P_{PV(t)}, \quad \text{for } t = 1, 2, \ldots, 168 \tag{11}$$

The $P_{demand(t)}$ is the electricity demand of Fælledby for a duration t, $P_{EV(t)(i)}$ is the charge or discharge power of an EV during the duration t. $P_{bought(t)}$ and $P_{sold(t)}$ are the power bought and sold during t, and lastly $P_{PV(t)}$ is the PV produced during t. In the V2B system, these were all the entities either contributing or consuming energy, and therefore the sum of these must always be zero to maintain the power balance.

This model included a total of 574 EVs, expected to charge and discharge independently. To achieve this, the model determined the charge or discharge rate for each EV individually and therefore the power of each EV was a decision variable, resulting in 574 individual decision variables.

For all of these decision variables to take on realistic values, a number of constraints were applied to ensure lifelike behavior of the model. The first constraint was the power balance seen in Equation 11 as this must be maintained to ensure realistic solutions. The other constraints were applied individually to the decision variables.

Power bought and power sold constraints

The bought and sold power had two individual constraints applied:

$$\begin{aligned}
0 \leq P_{bought(t)} &\leq P_{max}, \quad \text{for } t = 1, 2, \ldots, 168 \\
0 \leq P_{sold(t)} &\leq P_{max}, \quad \text{for } t = 1, 2, \ldots, 168 \\
P_{bought(t)} + P_{PV(t)} &\leq P_{max}, \quad \text{for } t = 1, 2, \ldots, 168
\end{aligned} \tag{12}$$

This was done to ensure that negative power was not bought or sold and that the power in the system did not exceed the maximum allowed of 3700 kW, defined in section 4.1.

EV power constraints
The first constraint was the availability of the EVs. The EVs could only charge and discharge when they were available, and their availability was derived from the driving habits in section 3.6.

$$E_{EV(t)(i)} = E_{EV(t)(i)} \times EV_{avialable(t)(i)} \quad \text{for } t = 1, 2, \ldots, 168 \quad \text{for } i = 1, 2, \ldots, 574 \tag{13}$$

The availability is binary, and if an EV was not available, no energy (E) could be transferred.

The second constraint for the EVs was their charge and discharge rate. These were given in section 4.1, and the constraints were applied to each EV every hour:

$$-11kW \leq P_{EV(i)(t)} \leq 11kW \quad \text{for } t = 1, 2, \ldots, 168 \quad \text{for } i = 1, 2, \ldots, 574 \tag{14}$$

This ensured that the EVs could not charge above or below the charge and discharge rate.

The third constraint was the modelling of the EVs' SOE based on the actual energy sent to and from the EVs' batteries. This was done with the charge and discharge efficiency. The model was quite large as it had many decision variables, and therefore modelling the efficiency was not straightforward. It was first attempted to apply the efficiencies based on whether the EV was charging or discharging with a binary indicator $is_{charging}$ that returned 1 when power was positive and 0 when power was negative:

$$\begin{aligned} E_{EV(i)(t)} = P_{EV(i)(t-1)} \times hr \times is_{charging(t-1)(i)} \times \eta_{charging} \\ +P_{EV(i)(t-1)} \times hr \times (1 - is_{charging(t-1)(i)}) \times \frac{1}{\eta_{discharging}} \\ \text{for } t = 1, 2, \ldots, 168 \quad , \text{for } i = 1, 2, \ldots, 574 \end{aligned} \tag{15}$$

The modelling of the energy sent to or from each EV battery was done by assuming that the power from the previous hour had remained constant for the entire duration. The energy amount could then be added or subtracted to determine the new SOE in the battery. However, this proved too complex for the model, and another approach to efficiency was taken.

Multiplying the $Power \times hour$ with $1/\eta_{discharging}$ would result in the correct discharge amount, but when the EV was charging, additional energy would be added to the EV. This was fixed using the binary value $is_{charging}$ again. But first, the difference between this approach and the actual charge energy had to be found:

$$\frac{11kWh}{0.9} - 11kWh \times 0.9 = 2.32kWh \tag{16}$$

Using $1/\eta_{discharging}$ would result in an energy increase of 2.32 kWh above the correct amount when charging at full power. This had to be removed, and to do that $is_{charging}$ was used:

$$\begin{aligned} EV_{E(i)(t)} = P_{EV(i)(t-1)} \times hr \times \frac{1}{\eta_{discharging}} - is_{charging(t-1)(i)} \times 2.32kWh \\ \text{for } t = 1, 2, \ldots, 168 \quad , \text{for } i = 1, 2, \ldots, 574 \end{aligned} \tag{17}$$

When the EV was discharging, $is_{charging}$ was zero, and the efficiency was applied, correcting the amount of energy pulled from the battery. When the EV was charging, 2.32 kWh was subtracted, resulting in a peak efficiency of 0.9 at 11 kW. The result of this method was a progressive charge efficiency that increased as the charge power approached the maximum charge power. The charge efficiency is illustrated below in Figure 11:

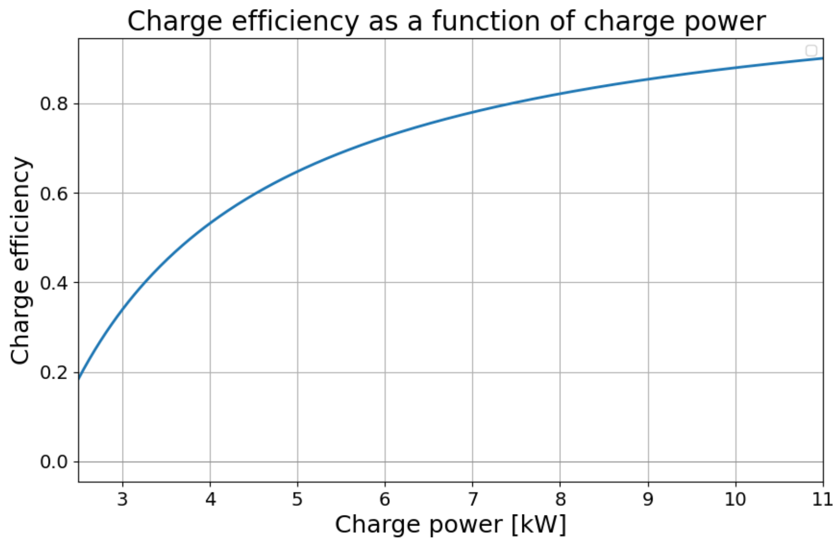

Figure 11: Relation between charge power and efficiency

Doing it this way had an additional bonus as it resembled real-life charging characteristics more than a flat efficiency. This is seen in [40] figure 3, where the charge efficiency increases along with the charge power. Ideally, this would be done for the discharge as well since it has the same characteristics, but this would further complicate the model and increase processing times. In this model, the EVs' discharge efficiency was set flat at 90%, while the charge efficiency was progressive as seen above.

EV SOC and SOE constraints

The first constraint was applying the initial SOE to every EV battery. This SOE was derived from the assumption in section 4.1 and was 20 kWh:

$$EV_{SOE(i)(0)} = 20kWh \quad ,\text{for } i = 1, 2, \ldots, 574 \tag{18}$$

Secondly, constraints were applied such that the energy in the battery could not be less than zero and more than the size of the battery:

$$0\% \leq EV_{SOC(i)(t)} \leq 100\% \quad \text{for } t = 1, 2, \ldots, 168 \quad ,\text{for } i = 1, 2, \ldots, 574 \tag{19}$$

Under V2B operation, additional constraints of minimum SOE and maximum SOC were applied:

$$\begin{aligned} 20kWh \leq Bat_{SOE(i)(t)} \quad & \text{for } t = 1, 2, \ldots, 168 \quad ,\text{for } i = 1, 2, \ldots, 574 \\ Bat_{SOC(i)(t)} \leq 80\% \quad & \text{for } t = 1, 2, \ldots, 168 \quad ,\text{for } i = 1, 2, \ldots, 574 \end{aligned} \tag{20}$$

These were applied such that under operation, the SOE could not go below 20 kWh and the SOC not above 80%, but if it was necessary for a trip, the SOC could increase above 80% and also drain the battery below 20 kWh while driving.

To continuously model the batteries' SOE, Equation 17 was used. The EVs' SOE was based on the SOE from the previous hour. To this, the charge/discharge power between the two hours was added.

This energy was then transformed to the actual energy subtracted or added to the battery using Equation 17. Lastly, the model checked if the car was driving during the current hour and subtracted the energy required to travel the simulated distance from section 3.6.

$$\begin{aligned} E_{\text{drive}(i)(t)} &= Distance_{(i)(t)} \times \eta_{\text{drive}} \\ E_{\text{charge/discharge}(i)(t)} &= P_{EV(i)(t-1)} \times hr \times \frac{1}{\eta_{\text{discharging}}} - is_{\text{charging}(t-1)(i)} \times 2.32 \\ EV_{SOE(i)(t)} &= EV_{SOE(i)(t-1)} + E_{\text{charge/discharge}(i)(t)} - E_{\text{drive}(i)(t)} \\ &\text{for } t = 1, 2, \ldots, 168 \quad , \text{for } i = 1, 2, \ldots, 574 \end{aligned} \tag{21}$$

With this constraint, every EV battery was modelled every hour, ensuring they did not exceed the charge and discharge rate of the system, and that the SOE and SOC boundaries of the EV battery were respected.

4.3 Stationary battery optimization

The model of the stationary battery was similar to the V2B model with the addition of the stationary battery and its decision variable $P_{stationarybat}$, which set the charge or discharge rate for an hour t. It was modelled the same way as the EV batteries, except that it was constantly available and was not depleted by driving. According to COWI, the cumulative capacity was 4,320 kWh, and the max charge and discharge rate was 3,240 kW. This also contributed energy to or from the system, and as such, the power balance equation was updated for the stationary battery optimization:

$$P_{demand(t)} + \sum_{i=1}^{574} P_{EV(t)(i)} + P_{bat(t)} = P_{bought(t)} - P_{sold(t)} + P_{PV(t)}, \quad \text{for } t = 1, 2, \ldots, 168 \tag{22}$$

As for the EVs, charge and discharge rate constraints were applied to the stationary battery:

$$-3240kW \leq P_{stationarybat(t)} \leq 3240kW, \quad \text{for } t = 1, 2, \ldots, 168 \tag{23}$$

Additionally, the minimum SOC for the stationary battery was 10% and the maximum 95%.

$$10\% \leq StationaryBat_{SOC(t)} \leq 95\%, \quad \text{for } t = 1, 2, \ldots, 168 \tag{24}$$

Like the V2B scenario only one week was modelled at a time, and therefore to not have too much "free" energy in the system, the initial SOC of the stationary battery was set to 20%.

$$StationaryBat_{SOC(0)} = 20\% \tag{25}$$

The SOE of the stationary battery was updated based on the previous SOE like it was done for the EVs. Since this was only one decision variable and not 574, the updated SOE was based on the initial EV SOE management from Equation 15.

$$\begin{aligned} E_{charge/discharge(t)} &= P_{Bat(t-1)} \times hr \times BatIsCharging(t-1) \times \eta_{charging} \\ &+ P_{Bat(t-1)} \times hr \times (1 - BatIsCharging(t-1)) \times \frac{1}{\eta_{discharging}} \\ Bat_{SOE(i)(t)} &= Bat_{SOE(i)(t-1)} + E_{charge/discharge(t)} \\ &\text{for } t = 1, 2, \ldots, 168 \end{aligned} \tag{26}$$

Lastly, the EVs' ability to discharge was removed by applying a lower bound charge rate of 0 kW:

$$0kW \leq P_{EV(i)(t)} \leq 11kW \quad \text{for } t = 1, 2, \ldots, 168 \quad \text{for } i = 1, 2, \ldots, 574 \tag{27}$$

With the introduction of the decision variable $P_{stationarybat}$, the stationary battery model was ready to be simulated with the same objective function from Equation 9.

4.4 V1G optimization

The V1G model was very similar to the V2B model with the only difference being the discharge rate. In the V1G scenario, the EVs could not discharge:

$$0kW \leq P_{EV(i)(t)} \leq 11kW \quad \text{for } t = 1, 2, \ldots, 168 \quad \text{for } i = 1, 2, \ldots, 574 \tag{28}$$

This one adjustment to the V2B optimization transformed it into the V1G optimization, as it only allowed the EVs to charge, but still did so when it was most cost-effective.

4.5 Running the optimization

The simulation was run by applying all constraints for every hour initially and then optimizing the best combined charge, discharge, buy, and sell strategy that resulted in the lowest cost given by the objective function in Equation 9. As stated in section 4.1, it is important to underscore that these models operated under perfect knowledge, and as such, this is the upper boundary or quite possibly above what can be expected in a real-world scenario. With that in mind, the analysis can begin.

5 Analysis

This section presents a comparison of the three simulated scenarios: V2B, V1G, and stationary battery. Each scenario represents a different approach to managing energy in systems integrated with electric vehicles.

5.1 Specifications about the simulated weeks

The model simulated and optimized a summer week and a winter week. The choice of these weeks was based on the average weekly PV production for their respective seasons. One additional condition was that the two chosen weeks had to start at 00:00 on Monday and end at 23:00 on Sunday. In 2020, the two weeks that most closely resembled the average were July 20 to July 27 and January 20 to January 27. The reason for choosing average weeks was linked to the plan to extrapolate to an entire year. If extremes of PV production were used in the simulated weeks, there would be even more uncertainty when scaling to a full year. Below are the specifications of the chosen weeks:

	Summer Week	**Winter Week**
Total PV production	150.67 MWh	13.84 MWh
Total consumption (without storage and EVs)	91.03 MWh	119.85 MWh
Average electricity buy price	1.918 DKK/kWh	2.259 DKK/kWh
Average electricity sell price	0.202 DKK/kWh	0.214 DKK/kWh
EV total driving distance	123,133 km	118,947 km

Table 10: Comparison of key metrics for simulated summer and winter weeks

The significant difference in PV production between the summer and winter week can be attributed primarily to the amount of sunlight available. During the summer, longer daylight hours and more intense sunlight lead to much higher PV production. In the winter, shorter days and lower solar intensity reduce PV production. Moreover, the PV panels low inclination of $\leq 30°$ (shown in Table 3) is more favorable for summer production when the sun is higher in the sky. The electricity consumption is higher in the winter week compared to the summer week, this is expected as the need for artificial lighting, heating, and other appliances increases. In summer, high solar production combined with lower consumption leads to more favourable conditions for energy surplus. In contrast, winter presents challenges with reduced PV output and increased consumption.

The two chosen weeks represent two different settings to evaluate the model and analyse the performance of the three scenarios. The two different settings are on the opposite side of the PV production and consumption spectrum and therefore give an in depth evaluation of the performance.

The average buying price for the winter week is higher than that of the summer week, this is expected, mainly due to the winter tariffs being higher than the summer tariffs as seen in Table 5. The average selling price for the winter week is slightly higher than the summer week, this is not a big difference which means the two settings have nearly the same selling price.

The EVs drive a combined distance of around 123,133 kilometers during summer and approximately 4000 less at 118,947 kilometers during winter. This is fairly similar and at an efficiency of 20kWh/100km around 24 MWh were spent driving the EVs.

5.1.1 Presentation of the hourly data

To fully understand and draw conclusions from the model outcomes, it is important to have a detailed understanding of the data over which the model is simulated. This section presents and comments on the hourly data used for the simulation of the three scenarios.

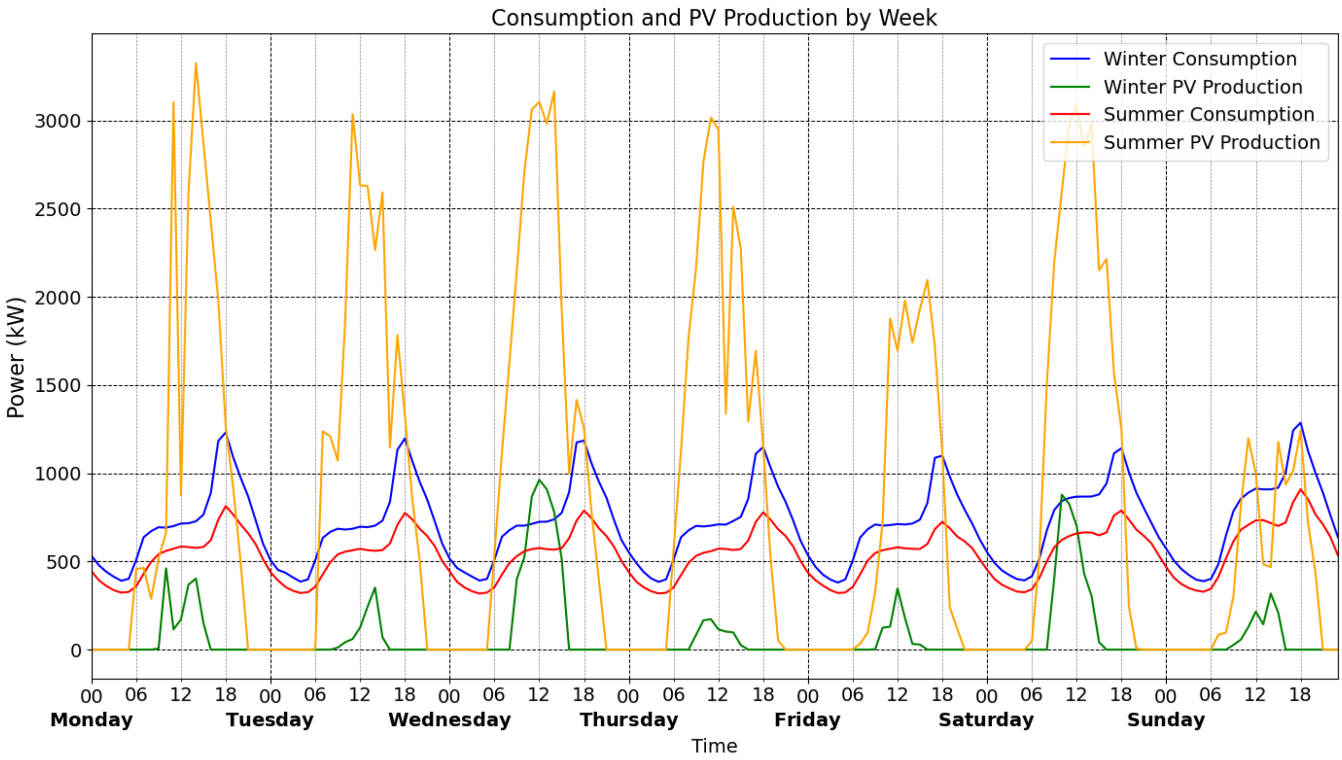

Figure 12: Consumption and PV production for summer and winter

The PV production during the summer week represents a typical summer week with sun and some clouds during the days. The deviation from an all-smooth PV production curve in the summer is due to the clouds which hinder the solar irradiation from reaching the PV panels. Notable is that the solar production on Friday and Sunday for the summer week is reduced compared to the other days, most likely due to bad weather. The winter week is influenced by mostly cloudy weather except for Wednesday and Saturday, these two days are mostly sunny, and provide more electricity to Fælledby than the other winter days.

The PV production in the summer week starts at 06:00 and ends at 21:00; in this period, the PV production is sufficient to cover the consumption at nearly all times. Whereas the winter week has shorter days where PV production starts at 09:00 and ends at 16:00. During this period, only a few hours of consumption are covered by the PV production.

The consumption for both the winter and summer week is consistently peaking at 18:00 and is lowest at 04:00. The consumption during the weekend stands out by having a higher consumption in the midday compared to the normal workdays because people are home.

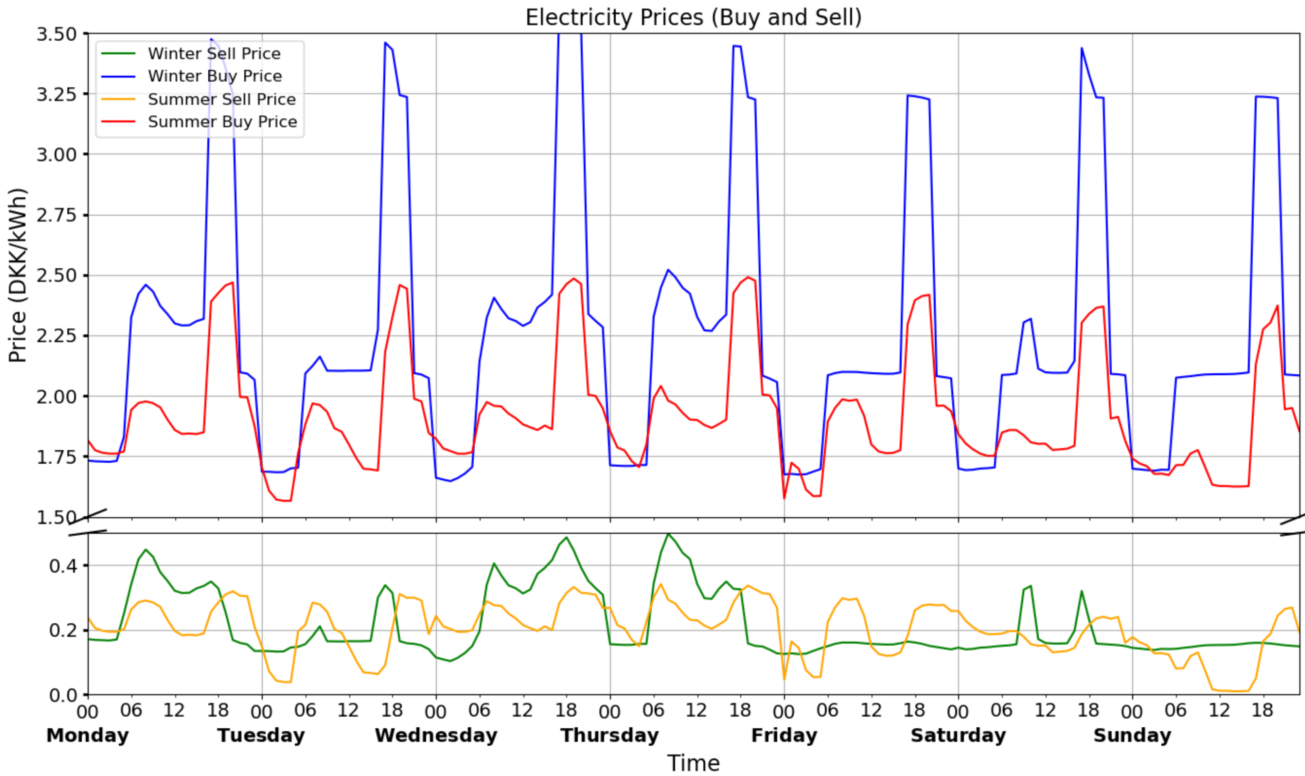

Figure 13: Buy and sell price Summer and Winter

The graph for the hourly buy and sell price for the summer and winter week shows the fluctuation of the prices throughout the chosen weeks. The daily tendencies of the buy price follow the tendencies in the consumption. Electricity is more expensive when the consumption is greater. This occurs mainly due to the variation in the DSO tariffs throughout the demand periods of the day shown in Table 5. The variation in the buy price makes it favorable to have energy storage, that can be deployed when prices are high. The buy price is significantly higher than the selling price. This means that it is favorable to use the produced PV electricity locally instead of selling it. The selling price is seen to move in the range of 0 DKK/kWh to 0.5 DKK/kWh. The difference from the peak buying price to the lowest buying price in winter is greater than that in the summer week, because of the seasonal differences in tariffs.

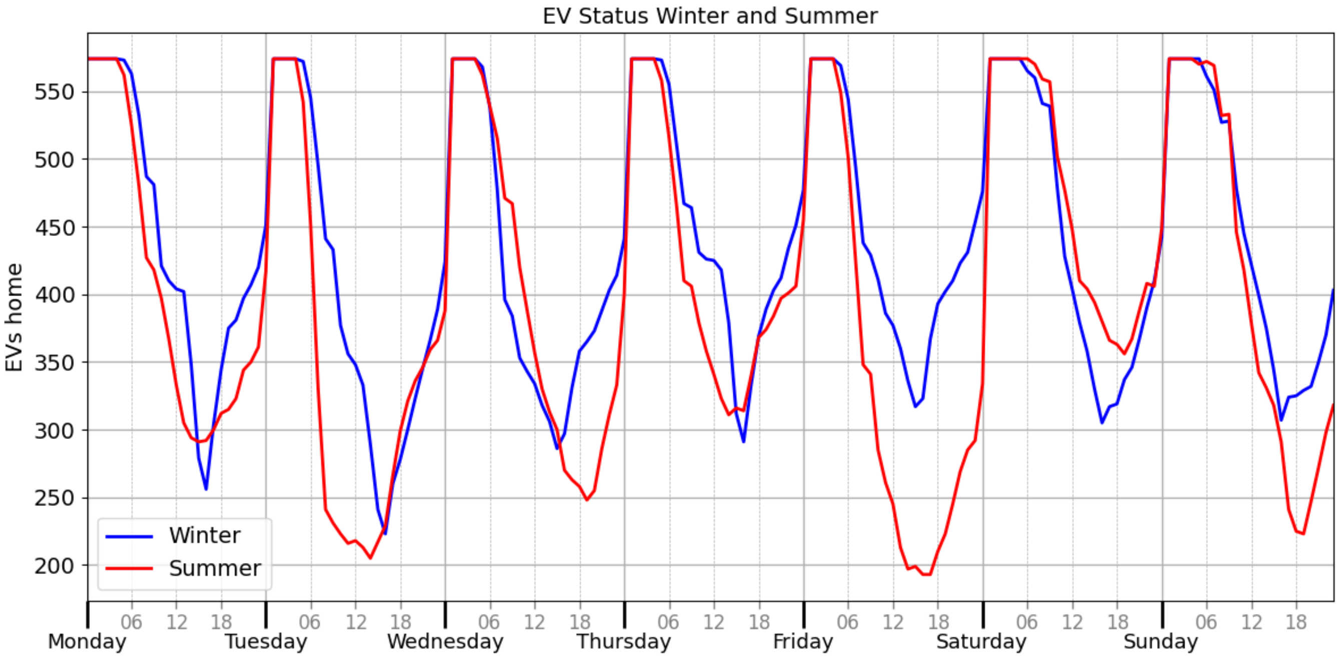

Figure 14: EVs home summer and winter week

The hourly EV availability in Fælledby is depicted in Figure 14 above for the summer and winter weeks. The EVs are home at night and then in the morning start to make their trips. Common to all days is that the EVs are home from 00:00 to 04:00. It is observed that the number of EVs away increases until the peak around 12:00 to 16:00, after which the trend reverses and the EVs start to return home. This plot shows the availability and, since it is assumed the EVs are available only after all trips are completed, the availability increases later during the day. The summer and winter weeks differ significantly on Friday, where more EVs are unavailable during the summer week.

5.2 Operation of the scenarios

This section will look into the operation of the scenarios during the winter and summer settings. It will analyze how each scenario manages to meet energy consumption demands by utilizing the decision variables. The analysis will focus on the strategic operations of each scenario, highlighting their effectiveness in utilizing available resources to optimize energy use and minimize costs.
When reviewing the graphs below, it is important to note that for the V2B and stationary Battery scenarios are capable of delivering power back to the energy community. Their respective power curves are negative during these instances. Opposite when the EVs or battery is charging, their curves will be positive.

5.2.1 Summer

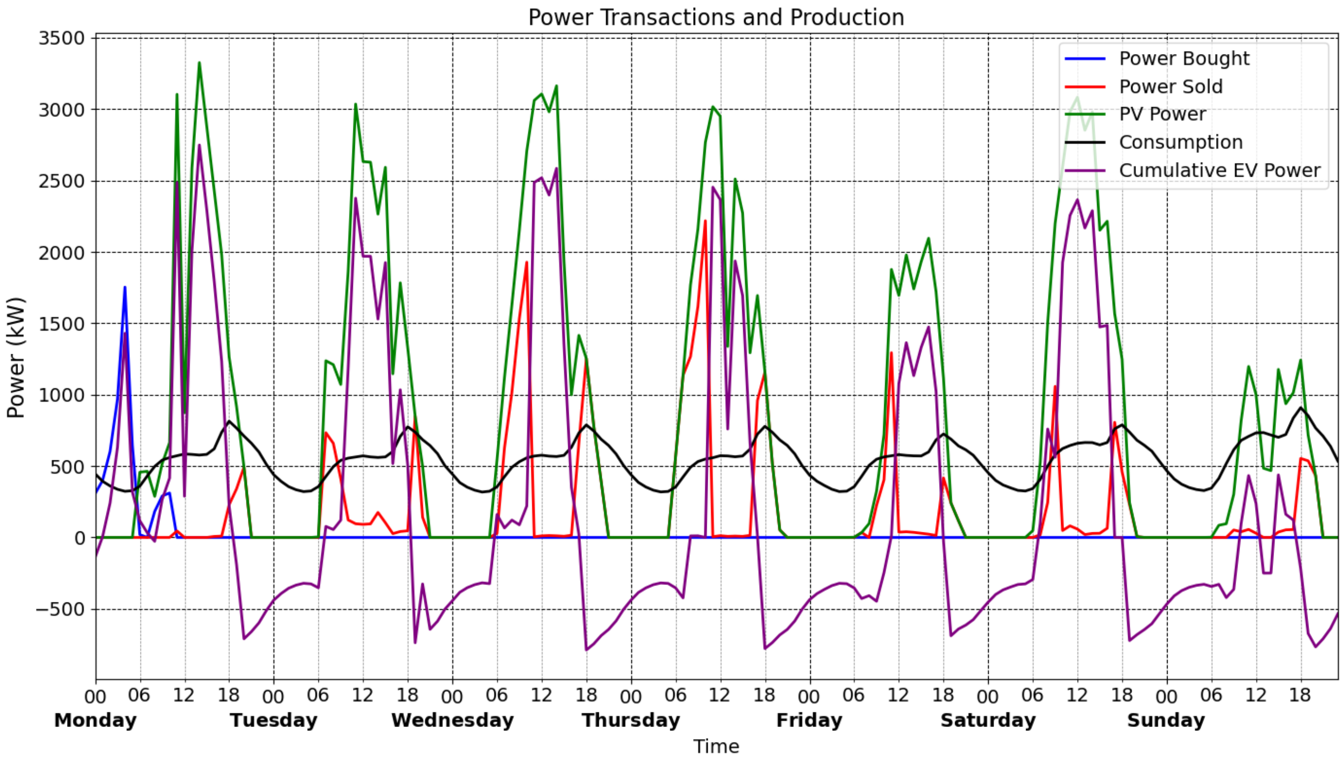

Figure 15: Overview V2B scenario summer

The power to and from the EVs and the power transactions for the V2B scenario are illustrated above. It shows how the scenario only buys power at the start of the week and then leverages the EVs to store power from the PV production. This stored power is then utilized, as indicated by the purple line, to cover consumption during periods when no PV power is produced.
There is a surplus of PV power during the summer week, exceeding the community's consumption needs, as seen in Table 10. The excess power from the PV production is strategically sold during the high sell price periods of the week, typically in the morning and at dinner time. The V2B scenario functions as intended in the summer week. The optimizer minimizes costs by strategically charging and discharging the EVs and capitalizes on favorable selling prices.

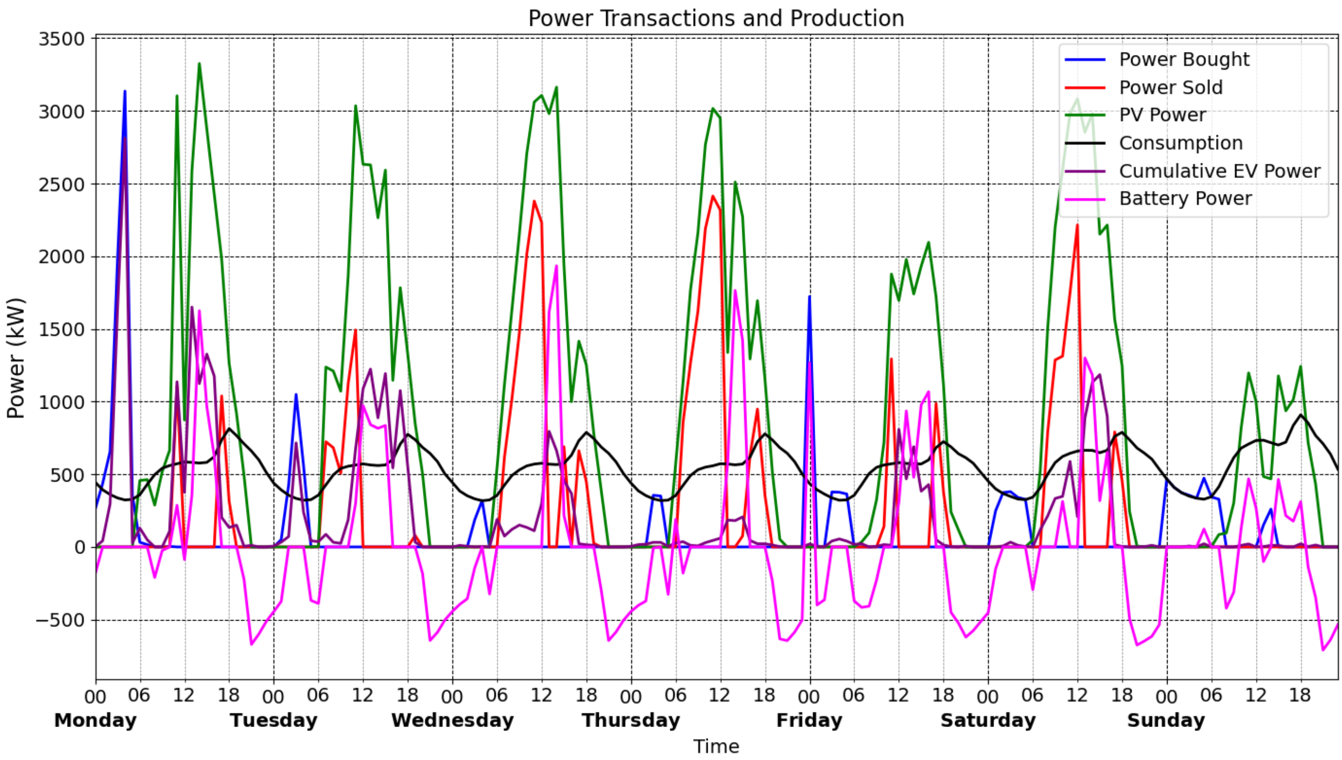

Figure 16: Overview Battery scenario summer

The battery activity and power transactions for the Battery scenario are depicted in the graph above. It is observed that the Battery scenario sells and buys more power than the V2B scenario, suggesting less efficient use of power generated from PV. The battery is strategically charged with PV power during the day and discharges to cover the nightly consumption. The battery can't cover the consumption the whole night, so power import occurs, typically around 3:00 when electricity prices are lowest. The EVs in the Battery scenario are charged during the day with PV power except for Monday and Tuesday mornings. Monday morning is explained by the low initial energy. The lack of sufficient PV power on Monday to simultaneously charge the battery, cover daily consumption, and fully charge the EVs for the following morning explains the need for power import on Tuesday morning. The Battery scenario works as expected and intended in the summer week.

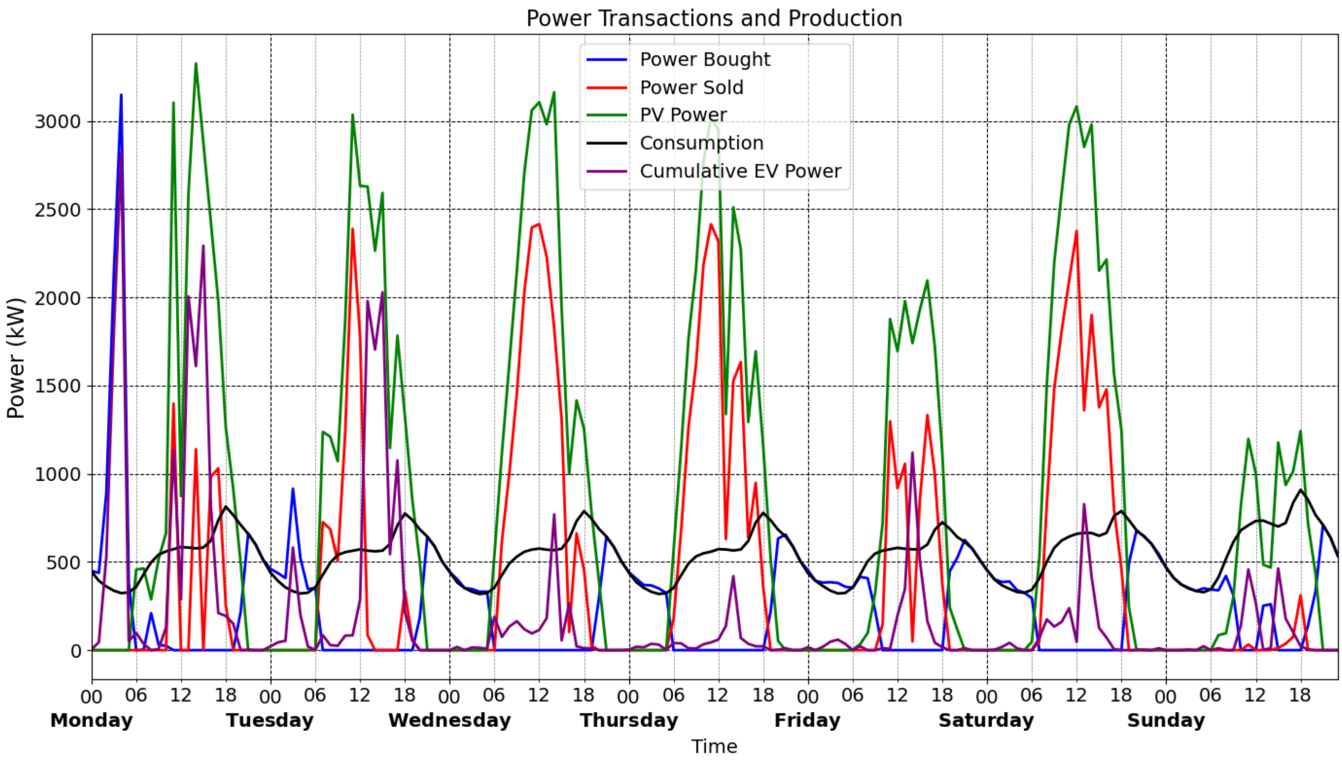

Figure 17: Overview V1G scenario summer

The power to the EVs and the power transactions for the V1G scenario are illustrated above. The lack of ability to store and deliver power back to the energy community is depicted by the absence of a negative power curve. The V1G scenario is forced to import power during non-PV production hours to cover the consumption, as expected. The proportion of PV sold increases after two days; this is explained by the EVs accumulating towards the 80% max SOC while charging with PV power during the first two days. This means that the EVs at home are close to full and can't receive as much PV power, so the power is sold in the absence of better options. The V1G scenario works as expected and intended in the summer week.

5.2.2 Winter

For all three scenarios in the winter week, it is observed that the import of power is capped at 3700 kW due to the grid connection limitations.

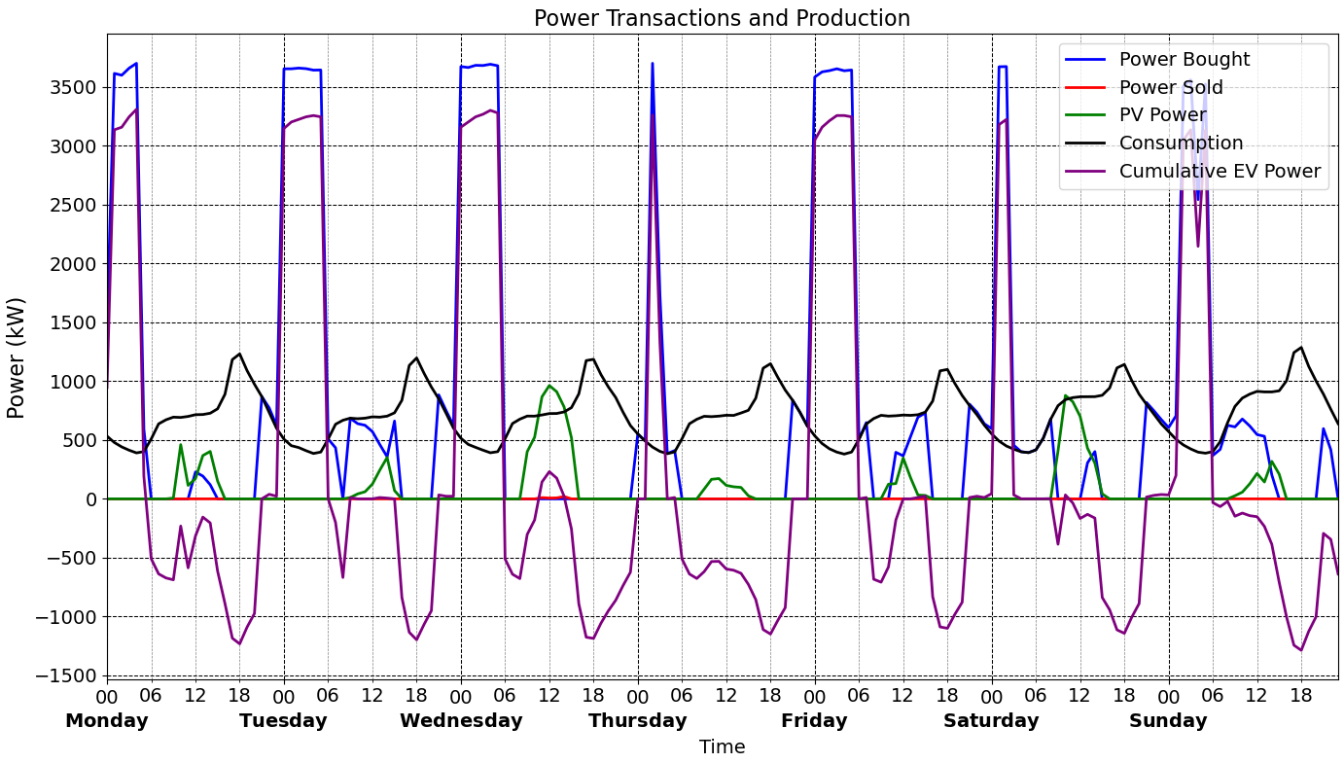

Figure 18: Overview V2B scenario winter

The power to and from the EVs and the power transactions for the V2B scenario are depicted above for the winter week. The EVs are charged at night during low electricity price periods and when the PV production exceeds the consumption. The EVs at home during the day provide power to the energy community by discharging. The amount of power discharged during the day differs; this can be explained by the EV availability shown in Figure 14. The day with the least amount of discharge during the day is Tuesday as it is also the day with the least amount of EVs home. Electricity imports are also observed around 12:00, with the exception of Wednesday and Thursday. On these two days, the energy stored in the EVs is sufficient to meet consumption needs until nightfall. The optimizer avoids importing electricity during periods with higher costs, demonstrating that it is functioning as intended. The V2B scenario functions as intended in the winter week and utilizes its storage capacity to minimize costs.

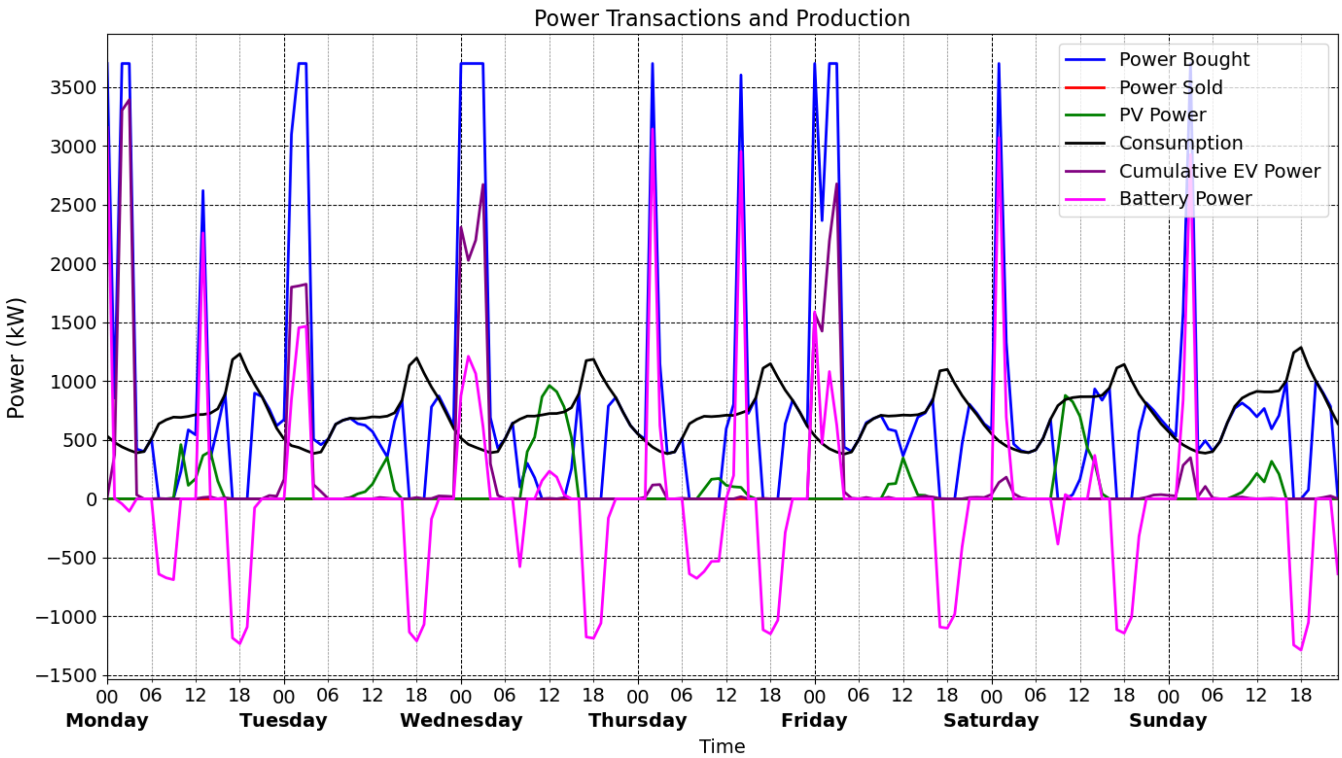

Figure 19: Overview Battery scenario winter

The battery activity and power transactions for the Battery scenario in winter are depicted in Figure 19 above. The battery always covers as much of the peak demand as it can, as seen by the discharging around these hours. Discharging in the morning around 08:00 occurs on Monday, Wednesday, Thursday, and Friday. This happens because the used energy can be replenished by PV power or power import at favorable prices before the peak demand. On Monday and Thursday, substantial discharge/charge cycles occur during the day. The higher morning price compared with the midday price on these two days makes a discharge/charge cycle feasible. The battery is hindered by its capacity and is not able to cover as much consumption as the V2B scenario. The capacity problem for the battery is looked into in section 6.1.1 later on. The EVs are charged mainly in the morning on Monday, Tuesday, Wednesday, and Friday because electricity prices are slightly lower than the rest of the days. The Battery scenario functions as intended in the winter week and utilizes its storage capacity to minimize costs.

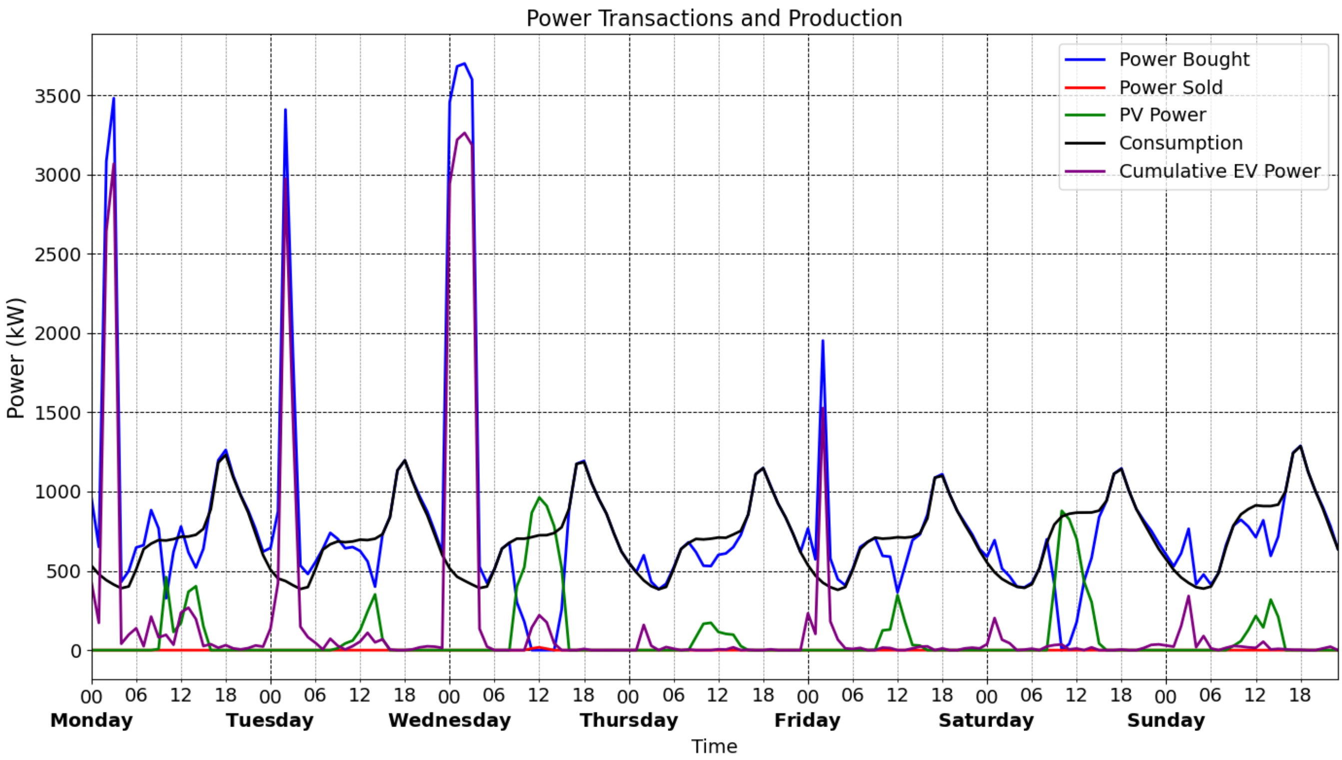

Figure 20: Overview V1G scenario winter

The power to the EVs and the power transactions for the V1G scenario are illustrated above for the winter week. The consumption is mainly covered by power import in the same hour as the consumption occurs. The PV production can cover some of the consumption during PV production hours, but because the production is so low, power import is necessary. No discharge of the EVs occurs as intended. Smart charging of the EVs is observed as planned, with charging predominantly occurring during low electricity price periods in the early hours of the day. The main days, for charging are Monday, Tuesday Wednesday and Friday as these days offer lower electricity prices as shown in Figure 13. Substantial charging is not needed every day since most EVs don't deplete their batteries enough while driving to require a daily recharge. A small amount of power import for charging happens during the day on Monday and Tuesday, which is not optimal for a smart charging strategy. This can be explained by the initial low SOE disturbing the first two days, making the EVs need more energy. Overall, the V1G scenario in the winter setting functions as intended.

5.3 PV utilization

It is interesting to compare how the scenarios utilize the PV production, especially in the summer week when production is high. This section investigates how the scenarios in the summer week utilize the produced PV electricity to cover consumption by looking at the amount of power sold. It is assumed that the power sold is a measurement of the PV utilization in the summer week. The rationale behind this assumption is that it is favorable to use the PV power and it is only sold in the absence of better options when doing the optimization. The total amount of power sold is shown in Table 11 below.

Scenario	**V2B**	**Battery**	**V1G**
Total Power sold [MWh]	30.5	42.7	69.0

Table 11: Total power sold

From Table 11, it can be derived that the V2B scenario has the best utilization of the PV production because it sells the least amount of power. The Battery scenario sells 12.2 MWh more than the V2B scenario and is the scenario with the second-best utilization of PV production. The V1G scenario sells the most energy and has the lowest utilization of PV production.

The utilization of the produced PV electricity is linked to the total cost each scenario endures because the revenue generated from selling a kWh of electricity does not equate to the cost of purchasing a kWh. The better PV utilization of the V2B scenario indicates that the technology can assist in filling gaps in fluctuating renewable energy production. The V2B technology's ability to store and redistribute energy supports the transition to a more CO2-neutral world because the reliance on conventional consistent power plants can be reduced.

6 Results

6.1 Total net cost

The main comparison criterion to evaluate the three scenarios were the cost of electricity. The total net costs are the overall expenses from buying electricity minus the revenues from selling electricity. The net costs for each scenario during summer and winter are shown in Table 12 below.

	V2B	**Battery**	**V1G**
Total net cost Summer [kr.]	1,823	20,948	66,848
Total net cost Winter [kr.]	251,248	270,431	313,951

Table 12: Total net Cost

The V2B scenario shows the lowest net cost in the summer week, making it the most economically efficient option when only the electricity bill is considered. The Battery scenario incurs higher costs but is still significantly less than the V1G scenario, which is the most expensive. The V2B scenario saves the energy community 19,125 Kr. during the summer week compared to the stationary battery system. The savings increase when compared with the V1G scenario, where the savings for the summer week amount to 65,025 Kr. The savings from the V2B and the battery storage scenario make a case for having energy storage in the energy community; this viability is investigated later.

The V2B scenario also has the lowest electricity cost of 251,248 Kr. in the winter week. This is a saving of 19,183 Kr. compared to the Battery scenario and 62,703 Kr. compared to the V1G scenario. The Battery scenario also has significant savings compared to the V1G baseline at 34,269 Kr. Again the savings from the V2B and the battery storage scenario make a case for having energy storage in the energy community because of the savings.

The total net cost indicates that the V2B scenario is better than the Battery and V1G scenarios at utilizing the electricity produced by the PV panels in the summer week. The V2B scenario also shows advantages in the winter week when little electricity from the PV is produced. This indicates that the V2B better exploits the fluctuating electricity price to Fælledby's advantage. A thorough analysis of the scenarios' net costs and their differences is conducted below by examining the hourly data.

The hourly net cost graphs below in Figure 21 and Figure 22 have the consumption curve depicted even though it does not match the cost unit. This is done to provide a better picture of when the costs are incurred compared to the demand. Revenue from selling occurs when the curves are negative, and costs occur when they are positive.

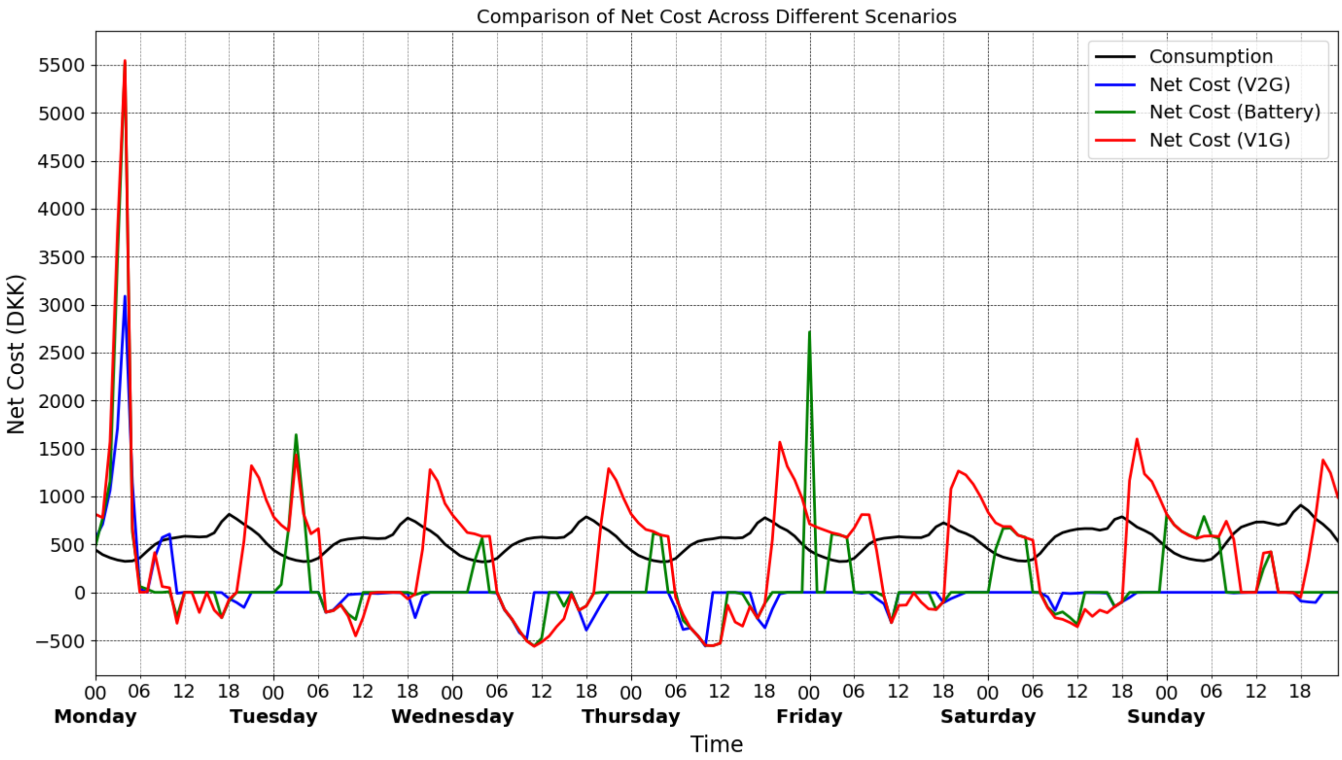

Figure 21: Net cost across the different scenarios summer

It is important to recognize that the revenue generated from selling one kWh of electricity does not equate to the cost of purchasing one kWh. This means that a greater amount of power must be sold to offset the expenses incurred from buying electricity. The biggest revenue spikes happen on Wednesday and Thursday for all scenarios. The amount of revenue these days reflects a high amount of power sold driven by substantial PV production on these days.

Looking at the hourly net cost for the summer setting, it is noticeable that the V2B scenario only imports electricity during the early hours of Monday. Likewise, the biggest spike in the net cost for the V1G and Battery scenario happens on Monday morning. This pattern is attributable to the initial state of energy in the EVs and the requirement to ensure sufficient energy in the EVs to make their trips in the morning. Tuesday and onwards the net cost seems to behave similarly all days. The V2B Scenario does not have to import any external electricity from the grid and only sells energy back to it. This means that the electricity produced by the PV and stored in the EVs doing V2B in the summer setting is sufficient to cover Fælledby's demand. The revenue from selling excess PV power cannot balance the big initial cost spike from Monday, so the V2B scenario ends up with a total cost of 1,823 Kr. as seen in Table 12.

Unlike the V2B scenario, the Battery scenario has to import energy from the grid during the entire week. The Battery scenario consistently buys electricity every night where the price is low. The amount of energy bought depends on the price and the PV production the following hours. If the production is low the day after more energy is bought during the night as seen Friday and Sunday morning. The import of energy in the Battery scenario happens in the cheapest hours and such that the hours of high prices are covered by the battery.

The V1G scenario imports and exports the most energy making it the scenario with the lowest utilization of the electricity produced by the PV. This scenario has the biggest revenue from selling excess PV power, but also the biggest cost from buying. The V1G scenario is forced to buy energy to cover the consumption, when no PV is produced. The most costly period for the V1G scenario occurs at around 20:00-21:00, here the PV stops generating electricity for the community, while consumption and electricity prices are still high. A cost spike on Tuesday morning stands out, this can be attributed to the EVs being charged at this time.

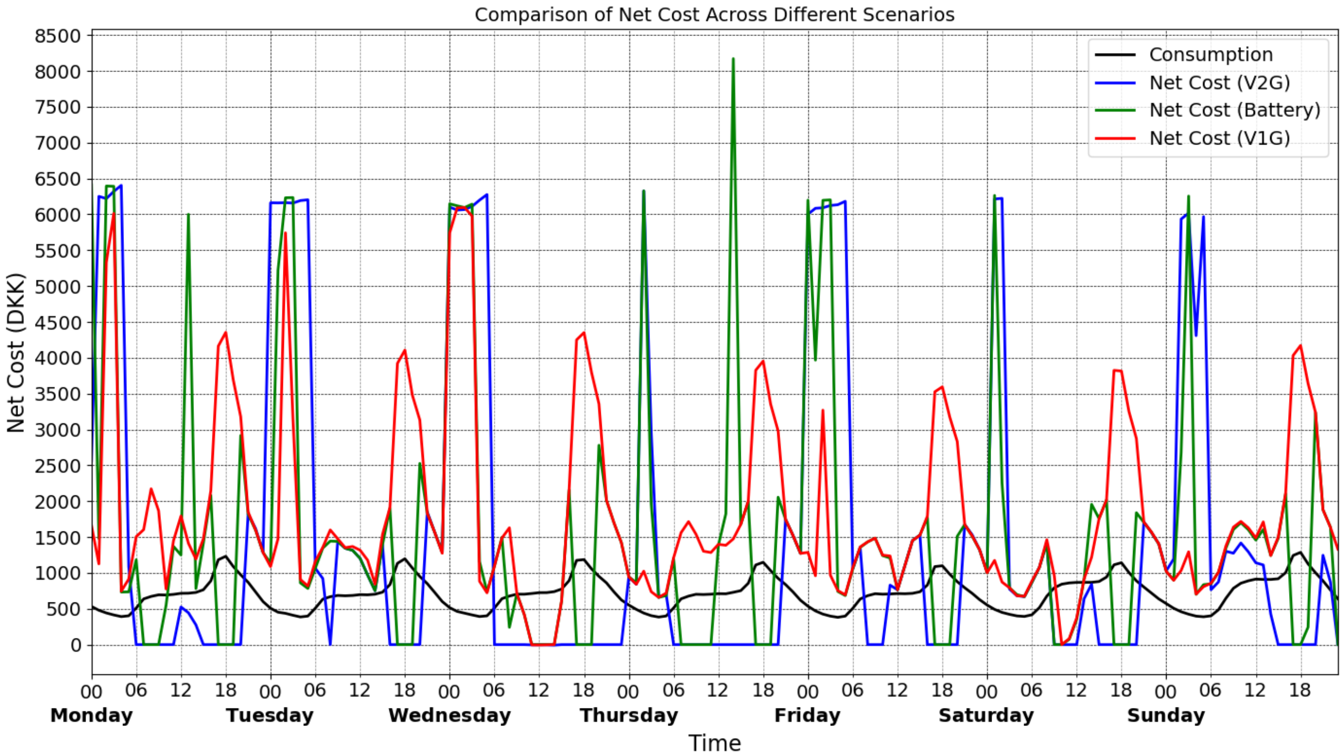

Figure 22: Net cost across the different scenarios winter

Looking at the hourly net cost for the winter setting a clear daily tendency for the three scenarios occurs. In general are all three scenarios has to undergo costs from importing electricity, but the time of this cost differs. Little to no electricity in the three scenarios in the winter week is sold to the national grid

The V2B scenario is consistently having the costliest period at approximately the same time of the day, this takes place at night hours during low periods of the electricity price. Costs from electricity imports are also observed during high hours around 12:00 but not nearly as substantial. The V2B scenario does not have to import electricity during the peak tariff hours from 17:00 to 21:00 and has enough stored energy in the EVs to supply and cover the most expensive periods. The value provided results in the V2B scenario having the lowest electricity cost during Winter.

The Battery scenario also shows consistent energy import in the cheapest hours of the day, but not as much as the V2B scenario. Shown in Figure 22 the Battery scenario endures a higher cost than the V2B during the day. This happens because the Battery system imports electricity during the day, such that the period of high tariffs can be covered by the energy stored in the battery. The battery has less total capacity than the EVs and therefore it can cover less of the hours with high tariffs. This means that the Battery scenarios' total net cost exceeds that of the V2B scenario as seen in Table 12. Notable is that the Battery scenario during Monday and Thursday endures a big cost in the middle of the day. This is from the discharge/charge cycle, the battery undergoes because of favourable prices.

The V1G scenario has no energy storage capacity and has to import power to cover the consumption when no PV is produced. It is seen that the V1G scenario consistently suffers a great expense at the most expensive hours of the day in the peak demand period between 17:00 and 21:00. The cost for the V1G scenario in the peak demand period stands out compared with the two other scenarios. It is mainly here the V1G scenario gets left behind and accumulates a more expensive total net cost.

6.1.1 Capacity in the storage for the Battery scenario

To look further into the reason why the V2B scenario outperforms the Battery scenario it is important to look at the hourly storage capacity of the stationary battery. The hourly storage capacity will show how much of the available storage capacity is used and if the total capacity is reached. It can then be determined if it is the Battery scenario storage capacity is holding it back from performing as well as the V2B scenario.

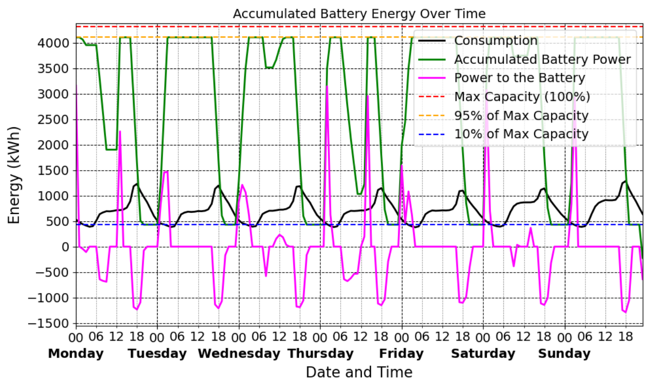

Figure 23: Battery scenario storage capacity winter

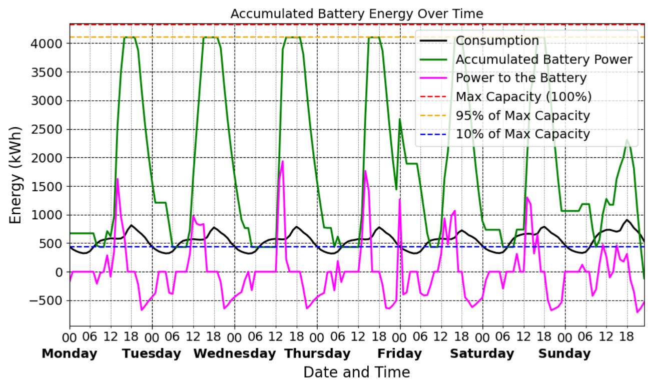

Figure 24: Battery scenario storage capacity summer

Looking at Figure 23 and Figure 24 it becomes clear that the Battery scenario is limited by the battery capacity of 4,320 kWh. It reaches 95% SOC quickly and therefore can't import more energy in the cheapest hours to use in the more expensive ones. Even tho the Battery scenario does not have the battery capacity to fully supply the more expensive hours it has the capacity to supply power in the peak demand period. In general, the battery utilizes its capacity to the optimum and works as intended. It draws power in the cheapest hours and supplies to cover consumption in the more expensive hours.
In the summer period, a similar pattern is seen, the capacity is reached during PV production hours resulting in less stored PV power. The capacity problem of the stationary battery gives less utilization of PV then the V2B scenario.
During the two simulated weeks, the lowest recorded number of cars home in the V2B scenario was 190, which is a total battery capacity of around 14,000 kWh. The main reason that the V2B scenario outperforms the Battery scenario is attributed to the difference in battery capacity.

6.2 Yearly scaling

The simulations were only run for a week of winter and a week of summer. To get an estimate of the yearly prices, the summer and winter weeks had to be scaled to a year. The thought behind this was that a combination of summer and winter weeks totaling 52 could resemble a year. The main difference between the summer and winter systems is the amount of PV produced, which affects prices a lot. Additionally, there is higher electricity consumption during winter, resulting in more cost. Therefore, PV production and consumption were the basis for scaling the winter and summer weeks to a full year. This was done by utilizing the ratio between PV production [MWh] and consumption [MWh] such that a combination of 52 summer and winter weeks had the same ratio of PV production and consumption as the entire year. The ratios were defined as below in equation 29:

$$\begin{aligned} ratio_{\text{winter week}} &= \frac{PV_{\text{winter week}}}{Consumption_{\text{winter week}}} \\ ratio_{\text{summer week}} &= \frac{PV_{\text{summer week}}}{Consumption_{\text{summer week}}} \end{aligned} \tag{29}$$

These ratios were then used to make the equation for scaling the system:

$$\begin{aligned} ratio_{\text{winter Week}} \times k1 + ratio_{\text{summer Week}} \times k2 &= ratio_{\text{year}} \times 52 \\ k1 + k2 &= 52 \end{aligned} \tag{30}$$

Solving these two equations resulted in:

$$\begin{aligned} k1 &= -52 \cdot \frac{\text{ratio}_{\text{summer week}} - \text{ratio}_{\text{year}}}{\text{ratio}_{\text{winter week}} - \text{ratio}_{\text{summer week}}} \\ k2 &= 52 \cdot \frac{\text{ratio}_{\text{winter week}} - \text{ratio}_{\text{year}}}{\text{ratio}_{\text{winter week}} - \text{ratio}_{\text{summer week}}} \end{aligned} \tag{31}$$

The summer and winter PV production and consumption from Table 10 was used and for the entire year the PV production was 4,6 GWh and the consumption was 5,8 GWh. Inputting this data in Equation 31 $k1$ and $k2$ were computed:

- $k1 = 28.9$
- $k2 = 23.1$

This means that to scale the winter and summer weeks to a year, 28.9 winter weeks and 23.1 summer weeks were required. k1 and k2 was then used to scale the weekly total net cost to the yearly total net cost for all three scenarios.

$$k1 \times Cost_{\text{winter week}} + k2 \times Cost_{\text{summer week}} = Cost_{annual} \tag{32}$$

These cost are seen in Table 13 below:

	V1G	**Battery**	**V2B**
Yearly total cost [**Million kr**]	10.617	8.659	7.303
Difference from baseline (V1G) [**Million kr**]	-	1.958 (-18.4%)	3.314 (-31.2%)
Yearly electricity cost per apartment [**kr**]	6,152	5,016	4,231
Average yearly savings per EV [**kr**]	-	-	5,773

Table 13: Yearly total net Cost

This shows how the weekly price difference stacks up, and there is a clear difference in price between all three scenarios. Since the V2B scenario was cheaper during summer and winter compared to the others, it is also the cheaper scenario for the entire year. Compared to the V1G scenario, the V2B saves over 3,000,000 Kr. annually. Additionally, the V2B scenario saves more than 1,300,000 Kr. the stationary battery system. As a result, the inhabitants of Fælledby would see a substantial decrease in their electricity bills. However, this does not take the capital cost (CAPEX) and operational cost (OPEX) into consideration. Before these are added, it is not possible to determine which system provides the most economic value.

6.3 Sensitivity analysis

The objective of the sensitivity analysis was to evaluate how much the number of EVs capable of V2B affects the net electricity price. The entire system hinges on having EVs available to charge and discharge, ensuring a lower electricity price. The sensitivity analysis shows the elasticity between the number of cars and electricity prices and should help determine how many EVs are necessary to create a viable business case. This sensitivity analysis was conducted for both summer and winter.

6.3.1 Methodology

The sensitivity analysis was conducted by only changing the number of EVs capable of V2B. The total number of EVs was kept consistent at 574. The V2B simulation model was kept exactly the same. In total, 13 simulations were run for summer and winter, with each step reducing the number of EVs capable of V2B. The first step reduced the amount by 24 EVs to a total of 550 EVs capable of V2B. Subsequently, each step reduced the number by 50 until 0 out of 574 were capable of V2B, equalling the V1G scenario. For each simulation, the price from the objective function was used as the result. Since a total of 26 optimizations were performed, the optimizer's accuracy was tuned down to yield results within a realistic time frame. Therefore, the results differed slightly from those in section 6.1.

6.3.2 Results

For winter and summer, the prices are shown in Table 14:

Num EVs V2B	0	50	100	150	200	250	300	350	400	450	500	550	574
Cost Winter $[kr.]$	311,336	298,255	285,721	274,054	265,692	262,242	260,460	258,841	257,133	255,411	253,855	252,351	251,745
Cost Summer $[kr.]$	74,080	54,934	36,482	22,667	12,630	9,226	5,114	4,240	3,831	2,873	2,415	1,868	1,579

Table 14: Table of electricity prices during Summer and Winter with varied amounts of EVs capable of V2B

From Table 14, it is evident that V2B provides a measurable positive difference in electricity prices. During winter, the cost of electricity with zero EVs capable of V2B was 311,336 kr, which is 59,591 kr (23.6%) more expensive than the scenario where all EVs were capable of V2B. During summer, the numerical difference is larger at 72,501 kr, but the percentage difference is 4,591%. The reason is that during summer, there is a significant amount of PV production, which keeps the electricity cost very low. The V2B systems that can distribute the production over the entire day need to buy very little electricity, resulting in a large percentage difference.

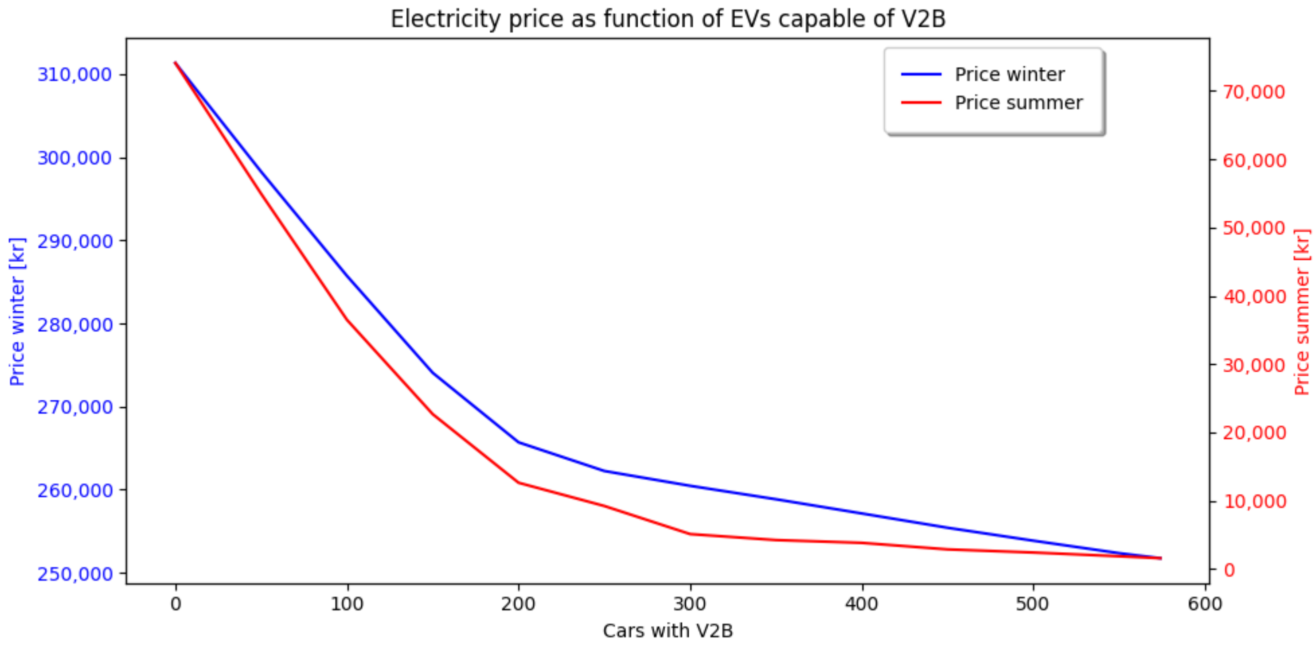

Figure 25: Electricity price during winter and summer weeks

More interesting is the investigation of the price behavior between these two extremes, as displayed in Figure 25 above. The relationship between price and V2B-capable EVs seems to behave similarly during summer and winter. Between the maximum of 574 and 300, both cost exhibit a slight linear increase, with the winter scenario line being slightly steeper. This indicates reasonable EV availability, as both summer and winter perform almost equivalently to the 574 EV scenario. However, when the number of EVs decreases below 300, the cost seems to increase exponentially. This suggests that there are not enough EVs in the system to consume excess PV production or peak shave during hours of high prices. As the number of V2B-capable EVs continues to decline, their ability to store excess PV and peak shave is reduced, resulting in a more drastic cost increase.

Depending on the additional cost of a DC bidirectional charger, installing 574 may not be the most efficient option cost-wise, as the additional gain in electricity cost reduction is minuscule between 574 and 300 V2B-capable EVs. This was further investigated in section 6.5.

6.4 Cost

This section analyzes the CAPEX and OPEX of the three systems. The goal is to compare the cost differences between the three scenarios, excluding common components like the PV system. The first step is identifying the unique parts of each system.

V1G system
The V1G system is the baseline system and does not have any unique components that are not present in the other systems.

Battery system
The obvious difference in the battery system is the stationary battery. Data from COWI estimates the stationary battery to cost 4456 kr./kWh, which is assumed to include installation, inverter, and battery management system. This brings the total capital cost to 19.25 million kr.
The operational cost is based on a 2015 study by the Australian Energy Market Commission [41] which estimated the operational cost of Lithium Ion batteries over 1 MW to be 13.1 AUD (60 kr.) per kW per year. With the battery capacity of 3240 kW, the operational cost is: $60kr./kW \times 3240kW = 194,400kr.$ annually.

V2B system
The difference between the V1G and the V2B system is the bidirectional charging. There are two scenarios for achieving bidirectional charging: using a type 2 AC charger or a DC charger capable of bidirectional charging. The first requires the car to perform the conversion between AC and DC and is the proposed solution by Renault [42]. The second solution has the charger performing the conversion, as is the case for Wallbox's DC bidirectional charger [34]. Using a standard type 2 AC charger would result in no additional cost for the V2B system. The DC bidirectional chargers are more expensive than regular chargers.

Wallbox has already brought a DC bidirectional charger to market. This was the Quasar 1, and they are currently working on Quasar 2 which has 11 kW DC bidirectional charging [34]. Through email correspondence, it was possible to get an estimate of 4500 USD (31,139 kr) without installation costs [43]. The installation cost of the V2B DC charger is assumed to be the same as a V1G charger. Further, it was assumed that each bidirectional charger replaces a V1G charger, as it can perform the same tasks. Therefore, the price difference between a bidirectional DC charger and a V1G charger is the additional cost in the V2B DC system.

The Fælledby project estimates a price of 20,000 kr per charger, including installation. Given that each charger has two plugs, the cost is 10,000 kr per charger output. The installation cost is assumed to be 2,000 kr, based on [44] where the installation cost is 2,999 kr, and further assuming there will be some discount when installing multiple chargers. The price difference between the AC charger and the DC charger is then roughly 23,000 Kr. With 574 bidirectional chargers, the additional CAPEX of the DC V2B system is 13,202,000 kr. The operational cost and lifetime of the AC and DC chargers are assumed to be the same. Hence, there are no additional operational costs for the V2B system.

Lifetime and discount rate

Both the battery system and the DC V2B system have a large CAPEX which far outweighs the operational cost. To figure out the Net Present Value (NPV) of these three scenarios (Stationary Battery, V2B with AC chargers, and V2B with DC chargers), a lifetime and a discount rate are required. The lifetime of the stationary battery is assumed to be 15 years. This is based on [45], which analyzed the lifetime of two state-of-the-art Li-ion batteries ($LiFePO_4$ (LFP) and $LiNIMn-CoO_2$ (NMC)) in a PV system. The system had a ratio of 1.2 between installed PV capacity [kW] and battery capacity [kWh], which closely resembles Fælledby's ratio of 1.1. In the study, the expected lifetime was 17.6 years for the LFP and 12.5 years for the NMC. The average of 15 years was used as the life expectancy of the battery in Fælledby. Both the AC and the DC chargers are assumed to have the same lifetime of 15 years. Lastly, the discount rate is assumed to be 5%.

6.5 Net Present Value of Battery and V2B system

The NPV is the metric used to determine the overall economic gain provided by the battery system and the V2B system. The NPV utilizes the CAPEX, OPEX, discount rate, and yearly savings to estimate whether the system is financially viable.

$$\text{NPV} = \sum_{t=0}^{T} \frac{C_t}{(1+r)^t} \tag{33}$$

C_t is the net revenue at year t, meaning that C_0 is -CAPEX, and at $C_t > 0$, the revenue is $Savings - OPEX$. The savings are the difference in electricity cost compared to the V1G scenario. r is the discount rate, and t is the time frame, which is determined by the battery and bidirectional chargers' lifetimes. The NPV is shown in Table 15 below:

	V2B AC charger	**V2B DC charger**	**Stationary battery**
NPV $[Kr]$	35,259,211	22,059,211	9,024

Table 15: Net Present Value of V2B and stationary battery system

This shows that there is a clear economic value in the V2B system regardless of which type of charger is used. The V2B system is a better investment than the stationary battery system, which barely surpasses the break-even point. The difference in NPV between the two charger types indicates that the CAPEX of the DC chargers results in a substantial difference.
From the sensitivity analysis, it was shown that reducing the number of EVs that could bidirectional charge did not significantly affect the cost initially. Assuming that all EVs can bidirectional charge, the limiting factor becomes the number of chargers capable of V2B. The variable in the sensitivity analysis function was changed from cars-with-V2B to chargers-capable-of-V2B, with this change the sensitivity function was used to predict new NPVs at different numbers of DC chargers.

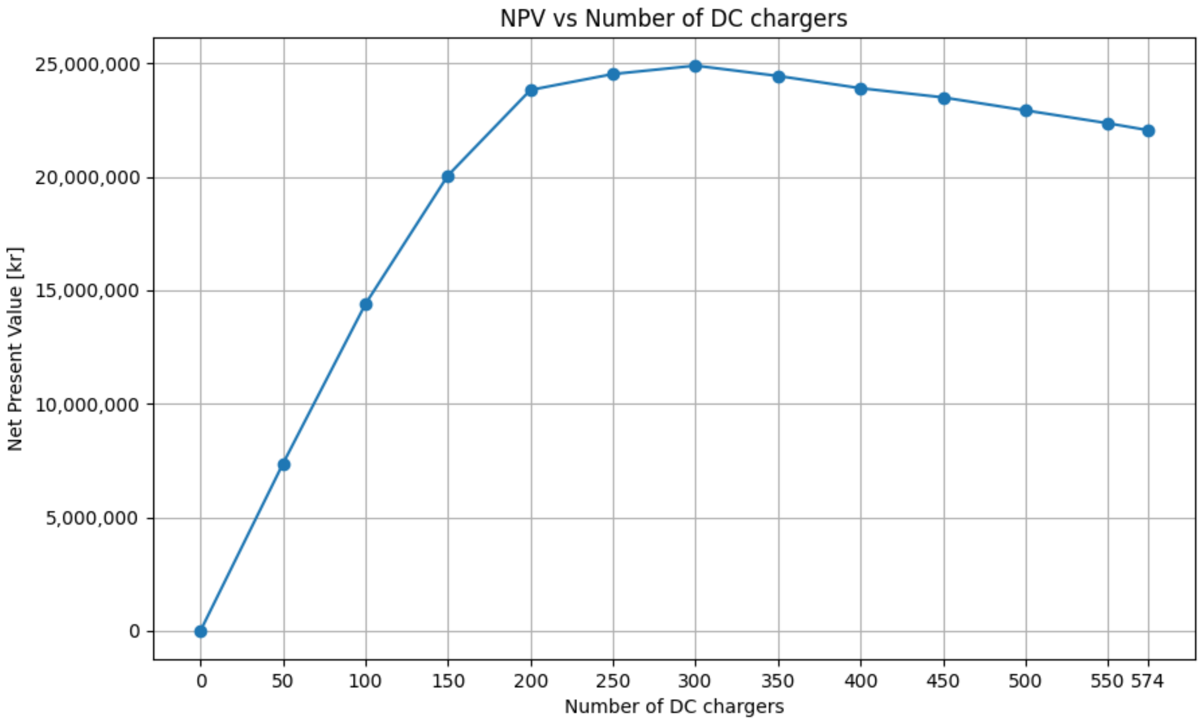

Figure 26: NPV as a function of total number of DC chargers

This shows that the ideal number of chargers is around 300, given a price difference of 23,000 kr between a DC and an AC charger. Decreasing the number of DC chargers to 300 results in an NPV 2,800,000 kr. higher than the NPV of 574 chargers. At 300 chargers the NPV peaks at 24,900,000 kr. The NPV is significant regardless of the type of charger used to facilitate bidirectional charging, and the V2B system has a strong business case.

7 Discussion

Perfect knowledge

The whole optimization model is based on perfect knowledge of the entire system. This includes EV driving patterns, consumption, PV production, and electricity prices. By assuming perfect knowledge, the thesis explores the theoretical limits and potentials of the system without the complexities of unpredictable variables. This sets a benchmark for what can be achieved under ideal conditions. However, the assumption of perfect knowledge reflects an unrealistic world where uncertainties are neglected.

One could ask how unrealistic the assumption of perfect knowledge is. Predictive tools and machine learning, such as neural networks, could be employed to estimate and continually update PV production, consumption, and electricity prices with high accuracy, a day ahead [39]. These tools can bring the theoretical perfect knowledge model closer to a real-world scenario.

Predicting the driving patterns of each EV to optimally utilize its storage capacity while ensuring it is ready for the next trip with sufficient energy is quite challenging. Accurately anticipating EV trips and distances depends heavily on the owner's willingness to provide detailed plans in advance. This expectation places a significant burden on the owner and may be overly demanding. An economic incentive for EV owners to provide their planned driving schedules ahead could potentially reduce the uncertainty in a real-world scenario for the driving patterns of the EVs.

While the assumption of perfect knowledge is unrealistic and does not fit a real-world scenario, modern technologies and incentives could make it not that far-fetched for a short period of time into the future.

Fælledby as the case

Having Fælledby as the case is a very favorable setting for a V2B scenario. One reason for this is the assumption that the driving patterns of its inhabitants mimic those of Copenhagen. The utilization of cars is relatively low in the municipality of Copenhagen when compared to other parts of Denmark because of attractive transport alternatives such as the metro. This means that the EVs have more hours plugged into the energy community where they can act as energy storage. This allows the EVs to capture the excess PV production and peak shave during hours of high electricity prices. In other parts of Denmark where cars are driven more often, there might not be the same availability. Energy communities outside of Copenhagen will most likely not gain equal value implementing V2B.

Assumptions

The assumptions presented in Table 9 significantly influence the results of this thesis. Particularly, the initial low state of energy (SOE) in the EVs heavily impacts the results as it forces the model to charge at the beginning of the weeks. The low initial SOE is consistent across all scenarios, neutralizing its effect when comparing costs between scenarios. Choosing a higher initial SOE would reduce the total cost for each scenario, but the relative savings between them would remain approximately the same. The EVs' charge and discharge efficiencies affect the losses in the system. The V2B scenario, which transfers the most electricity around the system, is most affected by changes in efficiencies. In the simulation, a flat discharge efficiency of 90% and a gradual charge efficiency peaking at 90% were used. This creates an upside for the V2B scenario, as the flat efficiency only impacts that scenario. This slightly inflates the results in favor of the V2B scenario.

Energy communities without PV
The V2B scenario in the winter week results in considerable savings. These savings are achieved without substantial PV production, indicating that the V2B scenario could also be economically feasible for energy communities lacking PV installations. This opens up new opportunities, not only for energy communities but also for ordinary buildings, to implement V2B technology.

Energy community legislation
The foundation of the economic value of implementing V2B in the Fælledby energy community relies on the ability to transport power within a microgrid, avoiding the national grid and its associated tariffs and taxes. This thesis assumes that it is possible to share power between buildings and the EVs parked in Fælledby. However, under current legislation, this is not permitted. Current regulations allow power sharing from one roof only under specific conditions: power may be shared among homes within the same building as the production facility or via an internal electricity connection to homes in one neighbouring building, but not simultaneously to both the building with the production facility and a neighbouring building [17].

For the assumption of power sharing within a microgrid to hold true, legislative changes are necessary. Efforts to amend the legislation have already started, though there are challenges that need to be addressed at the governmental level to make this viable on a larger scale. Currently, permissions are granted to local energy communities to engage in energy sharing under the condition that they serve as research bases for the relatively new technology [46]. This indicates government interest and is promising for the necessary changes to enable widespread power sharing within energy communities.

All three scenarios in this thesis rely on the microgrid assumption, but it is particularly advantageous for the V2B scenario because its main storage capacity is centralized under one roof in the underground parking.

V2G technology
The bidirectional charger technology used to perform V2B is seeing increased interest in regions with high penetration of renewable energy sources, such as Europe and parts of the United States. However, the technology is still not widely adopted as part of the mainstream EV infrastructure. This thesis assumes that the technology will have penetrated the EV market and is adapted into every EV in the danish market by 2035. This assumption may be an overestimate but players on the EV market have come out with statements about the technology integration in their plans, as explained in section 3.5. Most have already made plans for the integration, while some are a bit reluctant awaiting others progression. The assumption that the technology will penetrate the market before 2035 does not necessarily mean that every EV will have the capable technology for doing V2B. The older models still in use will have to be replaced by newer models with V2B capabilities. The amount of EVs in Fælledby with the sufficient technology in 2035 might be exaggerated but this is difficult to predict. However, as the sensitivity analysis showed in section 6.3 300 EVs capable of bidirectional charging yields almost the same results as the full 574 EVs. Therefore, a more conservative estimate of bidirectional charging adoption, will yield similar results.

Prediction power of the model
The optimization model operates under a lot of assumptions, resulting in uncertainties. The first significant of these is the already discussed perfect knowledge, resulting in an overestimation of value. Secondly, a winter week and a summer week are scaled to represent an entire year. However, the V2B scenario clearly outperforms the reference system (V1G) during summer and winter. The weekly

savings are very similar at 65,000 Kr. during summer and 63,000 Kr. during winter. One could argue that since the savings are equal during maximum and minimum PV production, the yearly scaling might not be too far off. Lastly, the driving habits also introduce some uncertainty, as they are based on the general population in Copenhagen. They might not fully be representative of the Fælledby inhabitants, who could be prone to drive more, as Fælledby is located a bit outside of Copenhagen. All in all, the optimization model is a good indicator of the business case, but most likely the results are inflated mainly due to the optimization running on perfect knowledge.

7.1 Future work

Building on the findings presented in this thesis, further exploration of various topics would be valuable to deepen the understanding of potential future uses for electric vehicles.

Further research into the accuracy of prediction tools, and how they can be used to predict data for an energy community hoping to utilize their storage capacity to the fullest, would be beneficial. The viability and feasibility of such tools will need to be investigated to build arguments for their incorporation into the optimization. Focusing on the prediction aspect, additional resources could be used to explore how to extract driving plans from the owners of the EVs and get them to cooperate. This would provide a better understanding of car utilization and more certainty when predicting driving habits.

Simulating without perfect knowledge would also be interesting, as it would give a more realistic picture of the value created by V2B. Incorporating prediction models of PV production, electricity prices, electricity consumption, and driving data could simulate a more true-to-life scenario. This would remove a lot of the uncertainty surrounding the model and provide a clearer estimation of value. Additionally, simulating an entire year could provide insights that might have been missed by doing just two weeks. In essence, future work mostly includes refining the models to increase the accuracy of predictions.

Considering the global perspective, conducting comparative studies in different settings, such as in the United States, could provide valuable insights. Analyzing the implementation and outcomes of electric vehicle technologies in front-runner countries could help the broader adoption of the technology worldwide. Additionally, the results of these international studies could pave the way for proper legislation, ensuring that the technology is both effectively integrated and regulated.

Getting EV owners to participate is also an interesting aspect. Implementing V2B will come at the expense of inconvenience to the EV owner. This inconvenience is two-fold, as the battery will experience some additional strain, and there will be uncertainty about the EV's driving range. Even though much of this can be mitigated through charge and discharge boundaries, there is a barrier to entry. Investigating methods to break this barrier would be interesting, as, in the end, the EV owner has to consent to the use of V2B.

8 Conclusion

In this study, the economic effect of including bidirectional charging-capable EVs in an energy community was investigated. This was done by optimizing the hourly charge and discharge rate of each individual EV and comparing it with a stationary battery system and a smart charging system. V2B clearly outperformed both the stationary battery system and the V1G system in cost.

Key findings:

- The simulations indicate that there is a clear economic benefit when implementing V2B. Considering all assumptions made, the NPV of the V2B system is still far greater than that of the stationary battery system and the V1G system. Both during winter and summer, the V2B scenario outperforms the other two scenarios. During summer, the large capacity of the EV fleet captures enough PV production to cover consumption during the night. During winter, there is enough EV availability to buy electricity when the price is low and deploy it when the price is high.

- The proposed stationary battery does not have enough storage capacity to cover periods when PV production is unavailable during summer. The same is true for winter, as there is not enough capacity to meet all consumption during hours of high prices.

- At around 300 EVs capable of V2B, the reduction in price tapers off, and each additional EV from there on reduces the electricity price minimally. Additionally, if DC chargers are used to facilitate bidirectional charging, 300 chargers seem optimal as they return the highest NPV.

- The system hinges on being able to share energy as an energy community. This is based on the assumption that energy communities become legal and that bidirectional charging is widely adopted by EVs. These advancements are therefore crucial for the economic feasibility of the system.

- Based on the driving patterns in Copenhagen, the large fleet of EVs was able to mitigate the discrepancy between EV availability during the day and PV production. During the two simulated weeks, the lowest recorded number of cars home was 190, which is a total battery capacity of around 14,000 kWh.

The findings suggest that bidirectional charging can play a vital role in the transition towards a more sustainable future. By utilizing the EVs' batteries for more than one purpose, the value they provide is increased, which is reflected in the electricity savings. Additionally, V2B helps utilize more of the PV production. The NPV found in this thesis is on the outskirts of what is feasible in reality, but the large difference when compared to the battery system and V1G system clearly demonstrates the value of the technology.

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