DTU Wind and Energy Systems

Optimization and techno-economic assesment of a residential prosumer

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Preface

This Bachelor's project was written at the Department of Wind and Energy Systems at the Technical University of Denmark in fulfillment of the requirements for acquiring a Bachelor of Science in General Engineering.

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Abstract

The proliferation of residential Distributed Energy Resources (DERs), especially photovoltaic (PV) installations and stationary storage systems, raises a number of important questions regarding their optimal operation. In the case of a PV installation, adding a battery to the system can improve both its profitability and decrease the prosumer's CO_2 footprint. The battery's impact depends on multiple aspects, such as the control strategy, optimization objective (if optimization is used), the effect of battery parameters and the inverter configuration. This project systematically examines the impact of these aspects on the economic and environmental benefit of the system. The foundation for the study is a real prosumer with such a PV-battery system.

The results show that a hybrid inverter shared between the PV and battery is to be preferred over a double inverter configuration where both components have their own inverter. This is both in terms costs and CO_2 emissions.

The benefit of an optimization-based control strategy over a rules-based heuristic depends on the objective function of the optimization. Cost optimization outperforms rules-based heuristics economically, but not emissions-wise. On the other hand, CO_2 optimization (where exported power is not given a CO_2 credit) outperforms the heuristics on emissions, but not on costs. Implementing an optimization-based control strategy leads to a greater number of battery cycles and therefore a shorter battery lifetime than in rules-based control, but this is compensated for by the increased profitability of the system in the case of cost optimization. The profitability of the system is greatly impacted by the system efficiency, with the battery capacity having a smaller but still appreciable impact. The emissions benefit is not as sensitive to these parameters as the economic benefit, even in the case of emissions optimization.

A multi-objective optimization that combines both cost and CO_2 optimization shows great potential, achieving both significant decreases in the prosumer's electricity costs and CO_2 footprint. Despite this, it can not be recommended over pure cost optimization because the high price of batteries mean that profitability should be the sole focus of a control strategy. For prosumers in Denmark, cost optimization leads to CO_2 footprint reductions anyway, due to the Danish energy mix. Ultimately though, it will be up the prosumer to decide which strategy to implement. By applying different weights to the emissions component of the multi-objective optimization, the prosumer can set the trade-off between profitability and emissions reductions according to their preference.

The residential energy system investigated in this project is located in Roskilde, Denmark and the benefits of the battery pertain to the specific prosumer. Nonetheless, these findings are expected to be similar for other prosumers, and the methodology employed in this project can be used in other case studies.

Acknowledgements

I would like to thank my supervisors Haris Ziras and Mattia Marinelli for helping me through this project. Their guidance has been invaluable.

An extra thanks is also due for them providing me with the prosumer data used in this project - without that, the project would not have been possible.

Contents

Nomenclature

Table 1: List of acronyms used in this project.

Acronym	Description
AC	Alternating Current
BMS	Battery Management System
DC	Direct Current
CET	Central European Time
DKK	Danish Krone
EMS	Energy Management System
LP	Linear Programming
MAPE	Mean Absolute Percentage Error
MILP	Mixed-Integer Linear Programming
NC	No (CO_2) Credit
PV	Photovoltaic
PVMS	Photovoltaic Management System
RE	Renewable Energy
RMSE	Root Mean Square Error
SCM	Self-Consumption Maximization
SOC	State of Charge
ToUA	Time-of-Use Arbitrage
UTC	Coordinated Universal Time
VAT	Value Added Tax
WC	With (CO_2) Credit

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1 Introduction

1.1 Background and Motivation

Over the last decades, man-made climate change and its causes and consequences has been a subject of increasing focus amongst scientists, policymakers and the public. The science shows that this anthropogenic climate change is driven primarily by global warming, which in turn is a result of greenhouse gas emissions from human activities. By far the most notorious greenhouse gas is carbon dioxide (CO_2), the atmospheric concentration of which has increased from 280 to 407 parts per million between 1750 and 2018. [1]

Reducing emissions is key to mitigating this climate change, and many nations have committed to this and adopted binding climate goals. Denmark for instance, has a goal of reducing its greenhouse gas emissions by 70% in 2030 compared to 1990 levels, and to be climate neutral, i.e. have no net emissions, by 2050. [2]

The largest historical source of CO2 emissions has been the electricity, heating and transport sectors, which combined account for over 60% of CO2 emissions in recent years [3]. To decrease these emissions, we have seen the advent and large-scale deployment of sustainable energy technologies such as wind turbines and solar panels in the electricity sector, and an increasing electrification of the heating and transport sectors. However, the intermittent generation nature of these renewable technologies and the variable nature of electrical demand present a challenge to electricity grids, warranting a need for flexibility in the power system [4]. Furthermore, the deployment of these renewables is still much too slow and the dependence on fossil fuels much too high, as the world is not on track to stay below a 1.5 °C or even a 2 °C warming scenario. [5]

There is a great potential in the residential sector, where consumers who are motivated by increasing electricity prices and energy security concerns may seek to optimize consumption habits and self-sufficiency, including installing their own energy resources. In the case of photovoltaic (PV) installations, the scalability and rapidly decreasing price [6] means that such installations are not only viable for commercial actors, but now also in residential settings. When paired with a battery, the intermittent generation of the PV can mitigated, increasing financial benefits for the consumer and flexibility in the power system.

This introduces the notion of *prosumers*, which are those who both produce and consume electricity. The *net-metering* concept, whereby the net result of production and consumption over a specified interval is considered, allows them to draw advantage of the pricing structure of electricity, and their ability to produce and store low-carbon electricity allows them to decrease the carbon footprint of their residential consumption.

To make such systems as attractive investments for prospective prosumers as possible, it is crucial to understand their operation and conduct a techno-economic analysis, as well as look into what can be done to further incentivize them.

1.2 Literature Review

The proliferation of residential Distributed Energy Resources (DERs), especially PV-battery installations, means home energy management systems have received considerable attention by researchers in the recent years. With prices for PV-battery installations projected to keep on falling and with BloombergNEF calling for a 20x increase in installed battery capacity by 2030 and an almost 80x increase by 2050 to meet their net-zero scenario, [7] it is a highly topical area of research. In this section, relevant research will be reviewed, organized into the overall areas that relate to the field. These are *flexibility resources*, *battery control strategies*, *temporal resolution* and *forecasting*.

1.2.1 Flexibility Resources

Batteries are not the only flexibility resource for increasing PV self-consumption. Demand side management, primarily via load shifting as well as other stationary storage solutions such as hot water tanks, are alternatives for residential PV installations. In [8], different on-site flexibility resources for balancing PV production and electrical demand are investigated. The resources considered are a heat pump with thermal storage, electrical storage (battery) and shiftable appliances. Two control strategies - rules-based and cost-optimal - are considered. The different flexibility strategies are used in a case study with empirical data from a real Finnish household, and the various configurations are simulated for a one-year period. Importantly, the authors find the battery and heat pump with storage to be the most effective flexibility measures. In [9], the potential of load shifting as a means of increasing self-consumption is shown to be low. These findings are corroborated by [10], where a battery is shown to improve PV self-consumption by 13-24% for every 0.5-1 kWh installed storage per kW PV power, whereas load shifting yielded a 2-15% increase in self-consumption.

In [11], thermal storage in the form of hot water tanks is compared with lithium-ion (Li-ion) and lead-acid (PbA) batteries and was found to economically outperform both batteries in UK households (with Li-ion outperforming PbA). Present-day Li-ion batteries however are over three times cheaper than assumed in the study, and these findings might change if the study was done now. Similarly, thermal storage systems were found to be more economically viable than batteries in [12], whereas batteries were found to improve self-sufficiency over thermal storage. Both [11] and [12] emphasize that the thermal storage benefit was largest when such a system was already installed, hence a comparison was made that effectively ignored the cost of installing thermal storage but accounting for the cost of installing a battery. For a fair comparison, the two systems should be compared including their upfront cost, and doing so might likely erode a significant part of the thermal storage advantage. The steadily decreasing battery costs [13] and increasing electrification of society means that home batteries are only becoming more attractive, and they are increasingly likely to become the standard means of stationary storage for residential DERs.

1.2.2 Battery Control Strategies

The authors of [8] consider two control strategies for the household - a rules-based approach that aims at maximizing PV self-consumption, either directly or indirectly, and a cost-optimal approach that minimizes the household's electricity cost. Compared to an inflexible reference control, the cost-optimal approach leads to a 13-25% reduction in the annual electricity bill, and an 8-88% decrease in electricity fed into the grid. In [14], two rules-based heuristics are compared - self-consumption maximization (SCM) and financial gain maximization (FGM). The study is based on real solar irradiance data and residential load profiles, but uses computationally simulated grid prices. The study compares the strategies across different storage sizes, and finds that each strategy performs significantly better than the other when it comes to its own target. Interestingly, the degree of self-consumption in the SCM strategy plateaus at a storage size equal to the average amount of daily PV and load, whereas the financial gain in the FGM strategy plateaus at a storage size of 50% of the average amount of daily PV and load. The diminishing returns of increasing battery size with regards to self-consumption are corroborated by [15] and [16].

A systematic review of seven different energy management strategies for small-scale PV-battery systems in Australia is conducted in Ref. [17]. Considered strategies include rule-based heuristics, such as SCM and time-of-use arbitrage (ToUA) along with a mix of the two, as well as optimization approaches using mixed integer linear programming (MILP) and dynamic programming (DP). The study also implements Policy function approximations, which are machine learning (ML) approaches. The practicalities of implementation, computational requirements, quality of input data and battery degradation are considered, and it is found that using a more sophisticated strategy does not necessarily result in a higher economic benefit when accounting for uncertainties in input data and battery degradation effects. The study uses half-hourly resolution data for the PV-battery systems, which can lead to inaccurate results, as shown in [18] and [19]. The study also only uses persistence forecasting in its optimization approaches, and focuses on optimizing for profits.

1.2.3 Temporal Resolution

The granularity of available data and the modelling done in a study can significantly impact results. If the resolution is low, then the battery loses out on arbitrage opportunities, since PV generation and load data is effectively smoothed, reducing both the number of opportunities and their magnitude. As shown in [18], such low temporal precisions can lead to noticeable underestimations of the economic benefit of PV-battery systems, with 30-minute and 60-minute resolutions yielding a mean relative error of 9.1% and 12.6%, respectively, when compared to a 5-second resolution. The authors find that a temporal resolution of 5 minutes or less is sufficient to compute accurate results. Ref. [19] agrees with this, showing that a 5 minute resolution is adequate for modelling purposes, after having studied the load and PV generation profiles of seven German households. Conversely, a low temporal resolution may lead to an overestimate of the degree of self-consumption and a corresponding underestimate of energy imports, as the authors of [20] show using real data from a Danish household.

1.2.4 Forecasting

Forecasting is pivotal for the energy management system (EMS) when it comes to battery scheduling. Simple rules-based heuristics can operate without forecasts, but more advanced heuristics and especially optimisation-based approaches will ultimately rely on forecasts in the real-time scheduling of a battery. This includes both load and PV generation forecasts, as well as electricity price and possibly grid CO_2 forecasts.

PV generation forecasts are a well-researched topic, and if a precise weather forecast is available, high degrees of accuracy can be achieved. Refs. [21] investigated the effects of erroneous weather forecasts on profitability and self-consumption, concluding that forecast uncertainty can reduce self-consumption by 0.5-5%. Meanwhile, [22] showed that batteries are able to mitigate the effects of inaccurate PV forecasts.

Load forecasts are more challenging, as loads are individual and entirely dependent on the habits of the person(s) inhabiting a household. As established in [23], realistic load profiles are needed for proper modelling, since aggregated profiles can lead to sub-optimal or misleading optimisation results.

In [24], a systematic review of different forecasts is conducted with regards to profitability, complexity and security using data from two prosumers in Denmark. The authors compare forecasts based on gradient-boosted decisions trees (GDBT) to naive persistence forecasts across both rules-based and optimization control strategies. They find that persistence-based optimization achieves 78% of the theoretical optimum profitability (computed using perfect forecasts) for one of the prosumers and 86% of the optimum for the other. The best-case GDBT-based optimizations achieve 90% and 93% for the two prosumers, respectively. A rules-based control strategy used as a benchmark yields 45% and 56% of the optima for the two, but is impervious to weather data and spot price manipulation, unlike the optimization-based strategies which rely on external data. The rules-based and persistence-based optimization approaches require the least computational power and have been, or can be, implemented practically in EMSs, whilst only some of the GDBTs are feasible to implement.

In summary, the review of related literature shows that while much work has been done on the topic, most studies evaluate battery control strategies based on their profitability, along with computational complexity as a secondary consideration. Many studies use small data sets with low temporal resolution, and some rely on computer generated datasets for load and PV profiles, as well as electricity prices. To the best of the author's knowledge, no work assesses several battery control strategies with regards to both profitability and emissions reductions, whilst also considering the whether the residential EMS shares one hybrid inverter or if the PV management system (PVMS) and battery management system (BMS) each have their own inverter.

1.3 Objectives

When assessing the benefit of a battery in a PV-battery system, there are numerous aspects to consider. Amongst other things, there are the battery control strategy (whether heuristic or optimization-based), optimization objective (cost minimization, emissions minimization, or multi-objective), the effect of battery parameters (capacity, power, efficiency, degradation) and whether the system shares one hybrid inverter or contains two inverters.

The possibilities for investigation in this topic are extensive, and in light of the limited time and computational resources available, the scope of the project will be defined clearly.

This project will focus on a household with a PV and battery system, and will investigate how various control strategies and battery parameters affect the battery's profitability and environmental impact, along with the implications of the system sharing one hybrid inverter versus each component having its own. The basis of this is a dataset from a residential prosumer located in Roskilde in the Eastern part of Denmark. Along with this, datasets on grid CO_2 emissions, both realized and forecasted, along with electricity spot prices will be used. Since the project focuses on the overall operation of the battery in the context of the EMS, battery chemistry and power electronics will not be investigated. The objectives of the project can be summarized as:

- Review and implement heuristic control strategies that do not employ forecasting or optimization
- Implement and test different forecasts
- Implement optimization-based control strategies assisted by forecasts
- Conduct a sensitivity analysis on the effect of battery parameters
- Provide recommendations for a residential prosumer

1.4 Outline

The project will be structured in the following manner:

- **Section 2** introduces the theoretical background and elaborates on the residential energy system
- **Section 3** presents the different battery control strategies, forecasts and modelling cases
- **Section 4** presents and discusses the results of the different inverter configurations and control strategies, and a sensitivity analysis is carried out
- **Section 5** discusses the findings in the broader context of residential energy systems
- **Section 6** concludes the project

2 Theory and Background

2.1 Electricity Cost Structure

In Denmark, the electricity price is composed of three main components - 1. energy costs, 2. fees and tariffs and 3. taxes. The energy cost is the cost of the electricity itself, and can be fixed or variable. Fees and tariffs are paid for the transmission and distribution of electricity, and can be volumetric or fixed. Lastly, taxes include a fixed electricity tax and Value Added Tax (VAT).

Energy cost, also known as the spot price, is determined on Nordpool, a pan-European power exchange that serves 15 countries across 21 bidding zones. Denmark has two bidding zones, *DK1* and *DK2*, which cover everything west and east of the Great Belt, respectively. On Nordpool, orders are matched to maximize social welfare while taking network constraints into consideration. That is, the clearing price for each hour and bidding zone is set at the intersection of the curves for buying and selling price. The day-ahead market functions as a closed auction and is used as a baseline for planning generation, and adjustments are then made in the intra-day market. Spot prices for the following day are typically published at 13:00 CET every day [25]. This means that on a given day, one always knows the prices for the rest of the day, and one also knows the prices for the following day if the time is 13:00 CET or past.

Fees and tariffs are split into two groups; a transmission system operator (TSO) tariff, and a distribution system operator (DSO) tariff. In Denmark, the TSO is *Energinet* and they are responsible for maintaining the electrical transmission infrastructure, and their tariff is split into a *net tariff* and a *system tariff*. The system tariff is paid partly via an annual subscription, whilst its remainder is paid for on a per-kWh basis along with the entire net tariff [26].

The DSOs are responsible for operating the distribution infrastructure. There are several in Denmark, and they each operate a local section of the grid. For the prosumer in this project (who is located in Roskilde), the DSO is *Radius A/S*. Their tariff is also split into a subscription, albeit on a montly basis, and the remainder is paid on a per-kWh basis [27]. Their tariffs are variable. Until 2023, the DSOs could use a flat or time-differentiated tariff, where the time-differentiated tariff had two values; a peak value for the evening hours in the winter half-year, and a normal value otherwise [28]. Since 2023, the Tariff Model 3.0 has allowed for the further differentiation of DSO tariffs to incentivize flexible power consumption in response to increasing electrification [29]. There are now 5 tariffs, split up by time of day and time of year and scaled in price as shown below:

Table 2.1: The different load periods in the Tariff Model 3.0.

Hour	00:00 - 06:00	06:00 - 17:00	17:00 - 21:00	21:00 - 00:00
Winter (all days)	Low	High	Peak	High
Summer (all days)	Low	High	Peak	High

Table 2.2: The scaling factors for price differentiation between the tariffs.

Hour	00:00 - 06:00	06:00 - 17:00	17:00 - 21:00	21:00 - 00:00
Winter (all days)	1/2	1	3	1
Summer (all days)	1/2	1/2	1.3	1/2

Taxes are the final cost component of electricity. This includes a state tax per kWh which changes periodically but is typically around 0.75 Danish kroner (DKK) / kWh [30], and finally VAT which is 25% on top of all other pricing components, i.e. the electricity price, tariffs and state tax. As of the time of writing, the TSO tariff is around 0.11 DKK / kWh [31], and the base DSO tariff is around 0.36 DKK / kWh [27]. The average electricity price for each hour of day in the DK2 bidding zone is plotted below for June 2023 and December 2023, to show the typical variation between hours and the significance of taxes and tariffs.

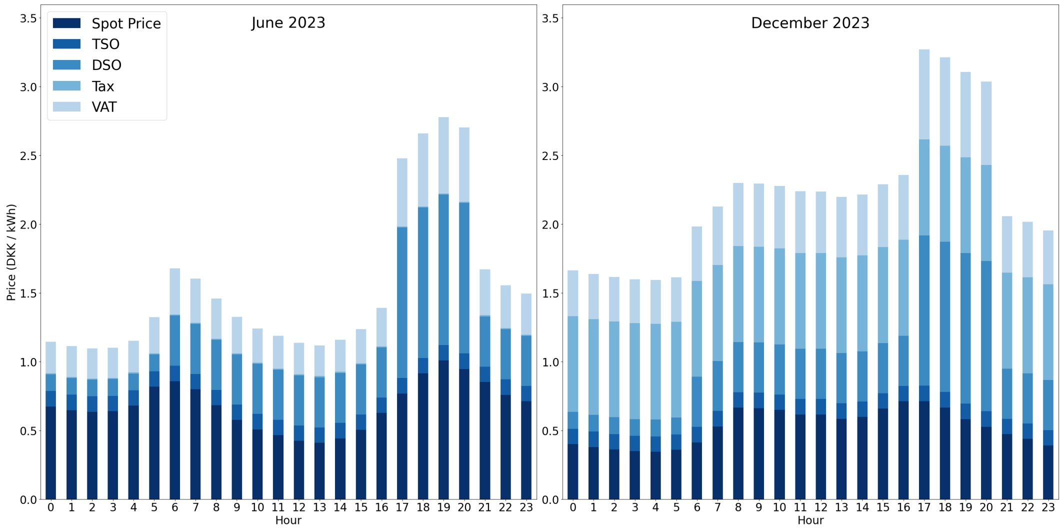

Figure 2.1: Average electricity cost component for each hour of June and December 2023.

Clearly, the spot price (i.e. the cost of the electricity from the producer) can end up being only a minor component of the final electricity price.

2.2 Net Metering

Net metering is an electricity billing mechanism whereby only net energy exchanges of prosumers with the grid over a specified interval are accounted for in settlements [20]. Originally implemented in Massachusetts in the United States [32], it has since gained popularity in multiple other countries, including Denmark. As per January 1, 2024, the netting interval is instantaneous for all prosumers in Denmark, whereas it has been hourly or even yearly in the past [33]. This effectively means that any imported electricity is now paid for in full and was implemented to more fairly spread the TSO and DSO costs across all consumers. Prior to this, the cost of maintaining the grid was borne disproportionately by regular consumers.

2.3 Battery Operation

Batteries are energy storage devices that convert chemical energy into electrical energy through electrochemical reactions. A typical battery consists of one or more electrochemical cells, each containing two electrodes, called the anode and the cathode, and an electrolyte that facilitates ion flow between them.

The anode always undergoes oxidation, which is a loss of electrons, and the cathode always undergoes reduction, which is a gain of electrons. During discharge, electrons flow from the negatively charged anode to the positively charged cathode through an external circuit, thereby providing current, while ions move through the electrolyte. During charging, an external power source drives the reverse reaction, where electrons flow from the now positively charged anode to the now negatively charged cathode, thereby storing chemical energy in the battery [34]. Current can only flow in one direction at a given point in time, and the battery can therefore not charge and discharge simultaneously.

The current flow in a battery is direct current (DC). This is characterized by a current flow that is steady in magnitude and direction, unlike alternating current (AC) where the magnitude and direction of current varies with time. Understanding the limitations of the battery is important for the project, even if it is treated as a black box in the modelling.

2.4 Optimization

Mathematical optimization is the field of finding the best decision variable(s) with respect to a criterion, termed an objective function, given a set of constraints. There are several types of optimization problems. The simplest is linear optimization, also known as linear programming (LP). In linear programming, the objective functions and constraints are all linear in nature, and the decision variables are (non-regative) real numbers. Some linear problems may restrict the variables to be integers, in which case the problem is known as integer programming. In mixed-integer linear programming (MILP), as implied by the name, some variables are constrained to be integers and others are allowed to be non-integers. Some variables can be futher constrained to be binaries, i.e. 0 or 1, in which case they represent decisions (such as whether to charge or discharge the battery in the context of this project).

2.5 Forecasting

Forecasting is the field of predicting future values, and is very important in energy applications. Forecasts can be generated in many ways, ranging from ML approaches such as neural networks and decision trees to statistical approaches such as ARIMA and SARIMAX models, to simple persistence forecasts. This project will use persistence forecasting to the extent it is necessary, which is the practice of predicting the future value of a variable to be its current or some previously observed value. This can be represented mathematically as:

$$\hat{y}_{t+1} = y_t \tag{2.1}$$

If there is a seasonality associated with the data, for example PV production, which exhibits a daily profile (typically peaking around noon when the sun is at its highest, and dropping to its lowest at night), the persistence forecast can be offset with some vallue δ. Suppose we have hourly values for PV production, then we might predict that the PV production at a time t as:

$$\hat{y}_t = y_{t-\delta} = y_{t-24} \tag{2.2}$$

Some of the important metrics concerned with evaluating forecasts are the mean average error (MAE) and the root mean square error (RMSE), defined as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{2.3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{2.4}$$

Here, y_i is an observed or realized value, $\hat{y}_i$ is the predicted value (corresponding to that observation) and n is the number of observations. Their difference is thus the error in the forecasted value, also known as a residual. Thus, for the MAE, the absolute errors are summed and then divided by the number of observations. For the RMSE, the square of the residuals is summed and the square root of this sum is taken, which gives weight to large outliers in the calculation. Both of these are measures of the errors between observed and forecasted values, and are in the same units as the values.

2.6 The Residential Energy System

In order to properly model the prosumer's PV-battery installation, it is important to understand the setup and energy flows in the system. The prosumer has a rooftop-mounted PV installation, stationary storage in the form of a battery and an EMS. An inverter serves both the PV installation and the battery, converting DC electricity into AC for consumption or exports to the grid. The PV and battery measurements are provided by the PVMS and the BMS respectively, and are fed to the EMS alongside external data such as forecasts that can be used to schedule battery operation. A smart meter keeps track of both grid imports and exports, and a utility meter is used for billing. The system can be illustrated succinctly with the following graphic:

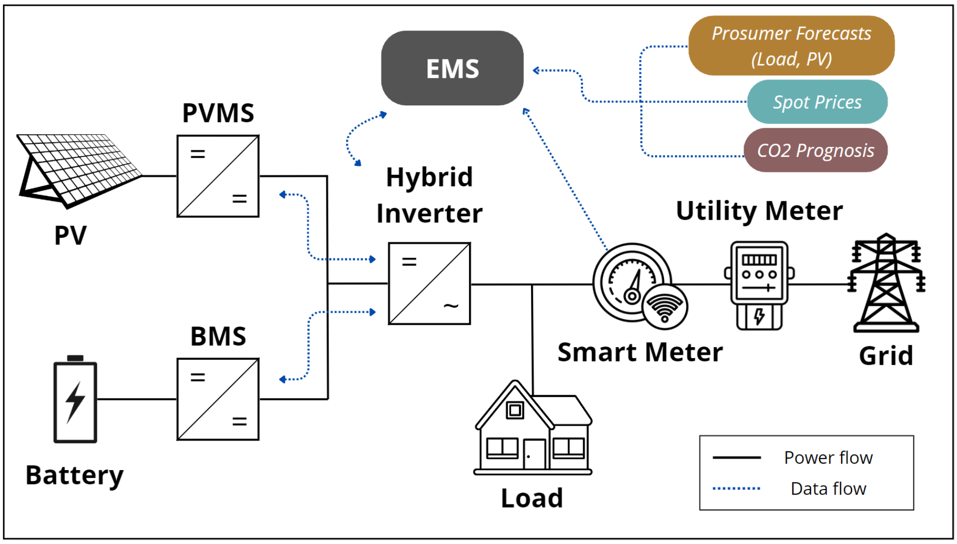

Figure 2.2: A schematic diagram of the prosumer's residential energy system.

Note that consumption and load both signify the electrical power usage of the household, and are used interchangeably henceforth. The prosumer paid 115000 DKK for the PV, battery and inverter in April 2021, of which the battery was just under half the total cost. The PV modules have a rating of 4.7 kW. The inverter, which is the Symo GEN24 5.0 by the Austrian company Fronius, has a capacity of $\overline{p}_{inv}$ = 5 kW [35]. The specifications for the battery, which is the BYD Battery-Box Premium HVS 7.7, are given below:

Table 2.3: Battery specifications for the prosumer. [36]

Description	Symbol	Value
Capacity	C	7.7 kWh
Max output current	$\overline{I}$	25 A
Peak output current	I_{peak}	50 A (3 s)
Nominal voltage	$V_{nominal}$	307.2 V
Operating voltage	V	240-360 V
Round-trip efficiency	η	≥ 96%

3 Methodology

With a proper insight into the prosumer's energy system and with the theoretical background in place, the PV-battery system can be modelled for different battery control strategies, forecasting types and inverter configurations to assess its economic and environmental performance. The combinations of these will result in the cases for this project.

3.1 Assumptions

In light of the project's scope and the limited time and computational resources available, assumptions are a necessity. The following assumptions are made:

- The battery is assumed to have a constant charging and discharging efficiency throughout the entire range of charging and discharging powers and at all levels of state of charge (SOC).
- The efficiency and capacity of the battery is assumed to be constant with respect to time, i.e. battery degradation is not accounted for.
- The inverter(s) are assumed to have a constant efficiency throughout the entire range of power throughputs.

The battery and power electronics will be treated as black boxes in the model, and the efficiencies and capacities as constants. In reality, the efficiencies of both the battery and inverter depend on many factors such as temperature, SOC and power throughput [17]. Battery capacity can also degrade significantly with time [37]. The assumptions are necessary for the formulation of the battery scheduling as a linear optimization problem, which is significantly easier to solve than a non-linear one. Since the project's main objective is to compare the different cases, it stands to reason that the results should hold also if these details were accounted for.

As a proxy for battery degradation, the number of cycles for each control strategy will be monitored, so the implications of different control strategies for the battery efficiency and lifetime can be discussed. The average SOC will also be kept track of. The sizing of the battery and inverter with respect to the PV installation will not be investigated, and is assumed to be appropriate.

3.2 Datasets

Prosumer Data. The prosumer dataset contains data 24 months of data in 5-minute intervals on the household energy balance, in the period 1/1/2021 00:00 - 31/12/2023 23:55. This includes *total energy consumption, direct consumption from PV, energy consumed from battery, energy from grid, PV production, energy to battery, energy to grid* and the battery *SOC*. The energy values are given in Wh, and are aggregates of each 5-minute interval. The total consumption and PV production are the variables of interest, since the aim is to the determine battery operation. Thus, the other datapoints are not used in this investigation.

Since the key values that are determined for a battery control strategy are charging and discharging power at every point in time, the energy values in the data (Wh) will be converted to an equivalent power (W). For this, the energy throughput for each 5-minute interval is converted to an average power, according to:

$$E = \int_{t_1}^{t_2} P(t)\,dt \Rightarrow P \int_{t_1}^{t_2} dt = P(t_2 - t_1) = P\Delta t$$

$$\Rightarrow P = \frac{E}{\Delta t}$$

For example, a PV production of 100 Wh in a 5-minute interval corresponds to 100 Wh / (5 minutes / 60 minutes/hour) = 1200 W of power in that interval. In reality, the instantaneous power in an interval will vary, but the conversion is made under the justification that the 5 minutes is a sufficiently fine resolution for the power to be more or less constant.

Spot prices. The spot prices are taken from Energinet's *Energi Data Service* [38], and they are hourly values, in DKK / MWh. The prosumer is located in Roskilde which is in the $DK2$ bidding area, so only data from this area is used. TSO tariffs are taken directly from Energinet [31], and tax values from Skat (the Danish tax authority) [30]. The DSO tariffs are also taken from Energi Data Service [39], such that the electricity buying price can be calculated.

CO_2 emissions. Data on CO_2 emissions, also from Energi Data Service, will be used [40]. These are values for the CO_2 emission in g-CO_2 / kWh associated with electricity consumed from the grid, with a 5-minute resolution. It can also be called the *grid CO_2 intensity*. Its value at a given time is based on emissions from the various power plants that are producing power at that time.

CO_2 emissions prognosis. Lastly, a dataset with a prognosis for the grid CO_2 emission will be used [41], also from Energi Data Service, which contains forecasted rather than actual values of the CO_2 emission but is otherwise the same as the just previously described CO_2 dataset. Thes values are published on a day-ahead basis at 15:00 CET every day [41].

3.3 Hybrid Inverter vs. Double Inverter

In Figure 2.2, a single 'hybrid' inverter is present in the residential energy system. This inverter is responsible for converting the DC power from the PV installation and the battery to AC power such that it can be used by loads in the house or exported to the grid. The inverter has a capacity of 5 kW, whereas the prosumer's battery has a max discharge power of 7.675 kW [36]. Thus, the inverter's capacity restricts the discharging rate of the battery. Also, since the inverter must both convert electricity from the PV and battery, potentially simultaneously, a further restriction arises. When discharging the battery, any PV production must go through the inverter (it cannot go to the battery since current cannot flow in and out of the battery simultaneously). Thus, when discharging the battery, the capacity of the inverter available to the battery is reduced by whatever the PV production may be.

This can limit system profitability in certain cases, and this project aims to find out how significant such a restriction may be. This restriction only arises when discharging; when the battery is being charged by the PV, the inverter is not involved.

On the other hand, if a double inverter setup is used, such that the PV and battery each have an appropriately-dimensioned inverter installed, the battery will always be able to discharge at its rated power. This can lead to increased self-consumption, profitability and a decreased carbon footprint of the residential consumption. A schematic of such a double inverter setup is shown below.

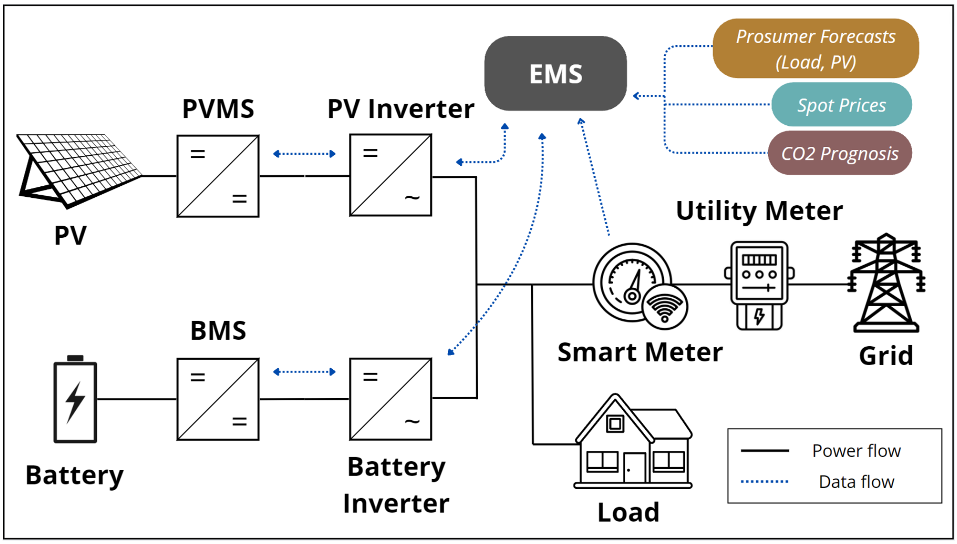

Figure 3.1: A schematic diagram of the system with the double inverter setup.

As an illustrative example, the restriction with the hybrid inverter could impact the prosumer in the following scenario. The inverter capacity is 5 kW, the PV installation 5 kW, and the battery's power rating is 8 kW. If the PV is producing 3 kW of power, all of which goes to the inverter, then the inverter only has 2 kW of capacity left. Thus, the battery can maximally discharge with 2 kW. If the spot price is very high and we wish to discharge to sell our stored energy, we are then limiting our revenue. Another scenario where the restriction might be a detriment is if consumption is very high. Suppose the PV is generating at 5 kW and going entirely to the load, such that the inverter is fully occupied. If there is still a power deficit, the battery cannot be discharged to cover this since the inverter is at capacity, meaning potentially expensive electricity needs to be imported.

3.4 Battery Control Strategies

This section will introduce the different battery control strategies used in the project. Overall, the control strategies can be divided into two groups; rules-based heuristics and optimization-based.

3.4.1 Rules-Based Heuristics

Rules-based heuristics are simple control strategies that follow a given set of rules, often characterized by a series of *if*-statements. They typically do not employ forecasting and do not actively seek to optimize a given outcome, but are easy to implement and usually do better than a random approach if they follow a set of rules that is consistent and logical. Two rules-based control strategies will be implemented in this project.

Self-Consumption Maximization

The first control strategy in this project is the so-called *self-consumption maximization* (SCM), which aims to maximize the self-consumption of a prosumer, and thereby minimize energy exchanges between the prosumer and the grid. It does this by always using the battery to its maximum extent before engaging with the grid. If there is a surplus in power generation, it charges the battery, only exporting once the battery is full. If there is a deficit in power, it discharges the battery, only importing from the grid once the battery is empty. In pseudocode, the algorithm is:

Algorithm 1: Self-consumption maximization

$s_t^{\mathrm{d}} \leftarrow s_{t-1} - \underline{s}$;
$s_t^{\mathrm{c}} \leftarrow \overline{s} - s_{t-1}$;
$p_t^{net} \leftarrow p_t^{\mathrm{L}} - p_t^{\mathrm{PV}}$;

if $p_t^{net} \geq 0$ **then**
    if *Inverter == 'Hybrid'* **then**
        $p_t^{\mathrm{d}} \leftarrow \min(\overline{p}_{inv} - p_t^{\mathrm{PV}}, p_t^{net}, s_t^{\mathrm{d}}/\Delta T \times \eta_d)$;
    else if *Inverter == 'Double'* **then**
        $p_t^{\mathrm{d}} \leftarrow \min(\overline{p}_{bat}, p_t^{net}, s_t^{\mathrm{d}}/\Delta T \times \eta_d)$;
    $p_t^{\mathrm{b}} \leftarrow p_t^{net} - p_t^{\mathrm{d}}$;
    $p_t^{\mathrm{s}} \leftarrow 0$;
    $p_t^{\mathrm{c}} \leftarrow 0$;
else
    $p_t^{\mathrm{c}} \leftarrow \min(\overline{p}_{inv}, -p_t^{net}, s_t^{\mathrm{c}}/\Delta T \times 1/\eta_c)$;
    $p_t^{\mathrm{s}} \leftarrow -p_t^{net} - p_t^{\mathrm{c}}$;
    $p_t^{\mathrm{b}} \leftarrow 0$;
    $p_t^{\mathrm{d}} \leftarrow 0$;
return p_t^{b}, p_t^{s}, p_t^{c}, p_t^{d};

Here, p_t^{L} and p_t^{PV} represent the average load and PV generation in the 5-min interval respectively, while their difference p^{net} is the net power demand. The upper and lower bounds on the SOC are denoted by $\overline{s}$ and $\underline{s}$ respectively, and the starting SOC by s_{t-1}. The energy that can be discharged from the battery is s_t^{d} and the energy that can be charged to the battery is s_t^{c}. These are divided by ΔT, which represents the normalized duration in which this energy must be charged or discharged, to get a corresponding power. Since the data is at a 5-minute resolution and we are working with kW and kWh, ΔT is equal to 1/12. The inverter power capacity is denoted by $\overline{p}_{inv}$, while $\overline{p}_{bat}$ denotes the battery power capacity. Finally, the charging and discharging efficiencies are represented by η_c and η_d, respectively.

Note the differences in the restriction on discharging power that arise in the hybrid vs. the double inverter configuration.

Time-of-use Arbitrage

Another rules-based approach is the *time-of-use arbitrage* (ToUA), which is effectively the self-consumption maximization algorithm with a caveat that tries to exploit the typical variation in spot prices. As shown in Figure 2.1, the spot prices have a tendency to rise in the evening hours, when demand is high and production from cheap sources such as wind and especially solar power is low. The prosumer could take advantage of this and sell any excess power directly to the grid rather than charging to the battery during these hours.

Due to the asymmetrical pricing of electricity, where the purchase price can be over an order of magnitude larger than the spot price that prosumers sell their electricity at, it is still wise to minimize imports, even during hours where spot prices and tariffs are typically low. Hence, the ToUA algorithm behaves like the SCM if there is a net consumption of power, and should always draw power from the battery before importing from the grid. Thus, the only change from SCM is when there is a net production of power, and the time is between 17:00 and 21:00 (chosen based on the spot price variation). The pseudocode for the algorithm is given below.

Note that is presented without the hybrid/double inverter *if*-statement for simplicity, but it is still present in the actual implementation of the algorithm.

Algorithm 2: Time-of-use Arbitrage

$s^{\mathrm{d}}_t \leftarrow s_{t-1} - \underline{s}$;
$s^{\mathrm{c}}_t \leftarrow \overline{s} - s_{t-1}$;
$p^{net}_t \leftarrow p^{\mathrm{L}}_t - p^{\mathrm{PV}}_t$;

if $p_{net} \geq 0$ **then**

$p^{\mathrm{d}}_t \leftarrow \min(\overline{p}_{inv} - p^{\mathrm{PV}}_t, p^{net}_t, s^{\mathrm{d}}_t / \Delta T \times \eta_d)$;
$p^{\mathrm{b}}_t \leftarrow p^{net}_t - p^{\mathrm{d}}_t$;
$p^{\mathrm{s}}_t \leftarrow 0$;
$p^{\mathrm{c}}_t \leftarrow 0$;

else

if $17 \leq hour \leq 21$ **then**

$p^{\mathrm{c}}_t = 0$;
$p^{\mathrm{s}}_t = -p^{net}_t$;
$p^{\mathrm{b}}_t \leftarrow 0$;
$p^{\mathrm{d}}_t \leftarrow 0$;

else

$p^{\mathrm{c}}_t \leftarrow \min(\overline{p}_{inv}, -p^{net}_t, s^{\mathrm{c}}_t / \Delta T \times 1/\eta_c)$;
$p^{\mathrm{s}}_t \leftarrow -p^{net}_t - p^{\mathrm{c}}_t$;
$p^{\mathrm{b}}_t \leftarrow 0$;
$p^{\mathrm{d}}_t \leftarrow 0$;

return p^{b}_t, p^{s}_t, p^{c}_t, p^{d}_t;

3.4.2 Optimization-Based

In this section, the optimization based strategies will be walked through. The aim is to schedule battery operation, for which the optimizer needs a forecast for the unknown values that appear in the optimization problem.

Prosumer Cost Optimization Problem

The cost optimization problem for a prosumer is presented below.

$$\min_{\mathbf{p}^{\mathrm{c}},\mathbf{p}^{\mathrm{d}},\mathbf{p}^{\mathrm{b}},\mathbf{p}^{\mathrm{s}},\mathbf{s},\boldsymbol{\delta},\boldsymbol{\sigma}} \quad \sum_{t\in\mathcal{T}} \left(p^{\mathrm{b}}_t \lambda^{\mathrm{b}}_t - p^{\mathrm{s}}_t \lambda^{\mathrm{s}}_t\right) \Delta T \tag{3.1a}$$

$$\text{s.t.} \quad p^{\mathrm{PV}}_t + p^{\mathrm{b}}_t + p^{\mathrm{d}}_t = p^{\mathrm{L}}_t + p^{\mathrm{s}}_t + p^{\mathrm{c}}_t, \quad \forall t \in \mathcal{T} \tag{3.1b}$$

$$s_t = s_{t-1} + p^{\mathrm{c}}_t \Delta T \eta_c - p^{\mathrm{d}}_t \Delta T / \eta_d, \quad \forall t > 1 \tag{3.1c}$$

$$s_1 = s^1, \quad s_n = s^n \tag{3.1d}$$

$$\underline{s} \leq s_t \leq \bar{s}, \quad \forall t \in \mathcal{T} \tag{3.1e}$$

$$0 \leq p^{\mathrm{c}}_t \leq \bar{p}(1-\delta_t), \quad 0 \leq p^{\mathrm{d}}_t \leq \bar{p}\delta_t, \quad \forall t \in \mathcal{T} \tag{3.1f}$$

$$0 \leq p^{\mathrm{b}}_t (1-\sigma_t), \quad 0 \leq p^{\mathrm{s}}_t \sigma_t, \quad \forall t \in \mathcal{T} \tag{3.1g}$$

Here $\mathbf{p}^c, \mathbf{p}^d, \mathbf{p}^b$ and $\mathbf{p}^s$ denote the vectors for charging power, discharging power, power bought and power sold, and $\mathbf{s}$ denotes the state-of-charge vector. Also, $\boldsymbol{\delta}$ and $\boldsymbol{\sigma}$ denote the binary charge-discharge and buy-sell vectors. These all have a length of n, which is the number of steps for which the problem is solved. These form the decision variables for the optimization. The set of steps in optimization horizon is denoted by $\mathcal{T}$.

The objective function is the power bought p_t^{b} times the buying price λ_t^{b} i.e. cost of power bought from the grid, minus the power sold p_t^{s} times the selling price λ_t^{s}, i.e. revenue from power sold to the grid. It is multiplied by a time interval ΔT such that the units are DKK. This objective function should be minimized such that net electricity costs are at a minimum - alternatively, one could multiply the function by -1 such that it represents net profit, in which case it should be maximized.

The first constraint (3.1b) is the power balance of the system, stating that the power introduced to the system (PV production, power imported from the grid and power from discharging the battery) should be equal to the power removed from the system (consumption, power exported to the grid and power to charging the battery). It is a consequence of the conservation of energy. The second constraint (3.1c) also arises from the conversation of energy, and states that the battery's SOC is equal to its SOC at the previous timestep, plus the energy charged and minus the energy discharged, whilst accounting for efficiencies.

The third and fourth constraints (3.1d) concern the SOC at the beginning and end of the optimization interval, denoted by s^1 and s^n respectively. The fifth constraint (3.1e) restricts the SOC to the upper and lower limits on SOC.

The sixth and seventh constraints (3.1f) restrict the charging and discharging power to be between zero and the upper limit (which depends on the inverter configuration), and make use of δ_t to represent whether the battery is discharging or charging. The eighth and ninth constraints (3.1g) stipulate that the power exchanged with the grid should be greater than or equal to zero, and make use of σ_t, which represents whether power is being sold to the grid or bought from the grid. All constraints apply to all timesteps t in the set $\mathcal{T}$, except 3.1c which does not apply to the first step.

Prosumer Emissions Optimization Problem

The cost objective function is not the only possible objective function. The CO_2 emitted by the prosumer is an alternative, which one would seek to minimize. Two possible objective functions are:

$$\min_{\mathbf{p}^{\mathrm{c}},\mathbf{p}^{\mathrm{d}},\mathbf{p}^{\mathrm{b}},\mathbf{p}^{\mathrm{s}},\mathbf{s},\boldsymbol{\delta},\boldsymbol{\sigma}} \quad \sum_{t\in\mathcal{T}} \left(p_t^{\mathrm{b}} \lambda_t^{\mathrm{CO_2}}\right) \Delta T \tag{3.2a}$$

$$\min_{\mathbf{p}^{\mathrm{c}},\mathbf{p}^{\mathrm{d}},\mathbf{p}^{\mathrm{b}},\mathbf{p}^{\mathrm{s}},\mathbf{s},\boldsymbol{\delta},\boldsymbol{\sigma}} \quad \sum_{t\in\mathcal{T}} \left(p_t^{\mathrm{b}} \lambda_t^{\mathrm{CO_2}} - p_t^{\mathrm{s}} \lambda_t^{\mathrm{CO_2}}\right) \Delta T \tag{3.2b}$$

The constraints are not listed, but are the exact same as (3.1b-3.1g) in the cost problem. The first function takes the power imported by the grid multiplied by the grid CO_2 intensity, and is thus a direct and intuitive measure of the CO_2 footprint associated with the prosumer's consumption from the grid. The second function is similar to 3.1a, giving a carbon credit to the prosumer when electricity is exported to the grid, akin to how the prosumer receives a monetary credit when selling electricity. The 'selling price' of the carbon credit is equal to the grid CO_2 intensity since the exported electricity can be assigned a carbon intensity of 0 g-CO_2 / kWh, due to there being no carbon emitted when electricity is produced from the PV array and/or discharged from the battery. Of course, the manufacturing and installation of the PV system (and battery) has a certain CO_2 emission associated it with it, but this is not included in the objective function in the same way the cost of the PV-battery system is not included in the cost function. Rather, these upfront 'costs' can be accounted for when evaluating whether the investment in a battery can be justified from an economic and environmental perspective.

In the event that the battery is charged with grid electricity and then sold back to the grid at a later time, the second objective function is still valid because the CO_2 of the charged electricity will have been 'paid' for when it was bought, meaning the full credit should be received when it is sold, leaving the net result just like with the cost.

The objective function that only accounts for CO_2 emitted from imported electricity, shown in eq. 3.2a will be called the *CO_2 no credit* objective function. CO_2 calculations done with this metric will be referred to as the *no credit* (NC) values. The objective function that also accounts for exported electricity, shown in eq. 3.2b, will be referred to as the *CO_2 with credit* function and CO_2 calculations done this way as *CO_2 with credit* (WC) values.

Note that emissions optimization and CO_2 optimization are used interchangably in this project.

The Multi-Objective Optimization Problem

A multi-objective optimization problem can also be considered, where the cost objective function is combined with one of the two emissions objective functions according to:

$$\min_{\mathbf{p}^{\mathrm{c}},\mathbf{p}^{\mathrm{d}},\mathbf{p}^{\mathrm{b}},\mathbf{p}^{\mathrm{s}},\mathbf{s},\boldsymbol{\delta},\boldsymbol{\sigma}} \quad \sum_{t\in\mathcal{T}} \left[(p_t^{\mathrm{b}}\lambda_t^{\mathrm{b}} - p_t^{\mathrm{s}}\lambda_t^{\mathrm{s}}) + k(p_t^{\mathrm{b}}\lambda_t^{\mathrm{CO_2}}) \right] \Delta T \tag{3.3a}$$

$$\min_{\mathbf{p}^{\mathrm{c}},\mathbf{p}^{\mathrm{d}},\mathbf{p}^{\mathrm{b}},\mathbf{p}^{\mathrm{s}},\mathbf{s},\boldsymbol{\delta},\boldsymbol{\sigma}} \quad \sum_{t\in\mathcal{T}} \left[(p_t^{\mathrm{b}}\lambda_t^{\mathrm{b}} - p_t^{\mathrm{s}}\lambda_t^{\mathrm{s}}) + k(p_t^{\mathrm{b}}\lambda_t^{\mathrm{CO_2}} - p_t^{\mathrm{s}}\lambda_t^{\mathrm{CO_2}}) \right] \Delta T \tag{3.3b}$$

Here, k is a constant that preserves dimensional homogeneity and determines the weight that the emissions aspect of the objective function should have with respect to the cost aspect. The constraints are the same as in the other optimization problems. To limit the scope of the project, only one version of the hybrid optimization problem will be considered in the results. The version of the emissions optimization problem that leads to better battery performance will be used in the hybrid problem. If 3.2a performs better, then 3.3a will be considered, and if 3.2b performs better, then 3.3b will be considered.

3.5 Forecasting

The optimization based control strategies are dependent on forecasts. The cost optimization problem needs spot prices, the emissions optimization problem needs grid CO_2 values, and the hybrid optimization problem needs both. All the optimization problems need PV and load values. This project will use publicly available forecasts supplemented by persistence forecasts where necessary.

Persistence Forecasts. For PV generation, load, spot prices and grid CO_2 intensity, daily and weekly persistence forecasts are considered for use in the optimization. Energinet's grid CO_2 intensity prognosis is also considered, and the day-ahead spot prices are mentioned in Table 3.3 for completeness. The RMSE and MAE for each is shown below, with the forecast that will be used for modelling shaded in green:

Table 3.1: Load

Look-Back	RMSE	MAE
Daily	0.602	0.297
Weekly	0.606	0.300

Table 3.2: PV

Look-Back	RMSE	MAE
Daily	0.668	0.285
Weekly	0.711	0.316

Table 3.3: Spot prices

Look-Back	RMSE	MAE
Daily	0.568	0.373
Weekly	0.777	0.546
Day-Ahead	-	-

Table 3.4: CO_2

Look-Back	RMSE	MAE
Daily	62.0	43.8
Weekly	80.7	58.6
Prognosis	10.7	7.5

The weekly and daily persistence load forecast have virtually the same error as shown in Table 3.1. This is due to the habits of the specific prosumer in this project, who exhibits regular consumption habits regardless of whether it is the weekend or a weekday. In general though, residential load profiles tend to exhibit a weekly seasonality. The exception is if a prosumer is away from home for an extended period, then there will be a larger delay in the weekly persistence forecast picking up on this, and the same goes if the prosumer returns home after an extended period away. Nonetheless, the two forecasts are very similar and the effect of choosing either on the results will be negligible. The weekly persistence forecast for loads will be used going forward.

The daily persistence clearly outperforms the weekly persistence for both RMSE and MAE in the other cases. Daily persistence being better for PV generation makes sense; PV generation is highly dependent on the weather, especially cloud cover, which is much more likely to be the same from one day to the next rather than one week to the next. As a secondary point, the number of daylight minutes can change appreciably from week to week in a country of Denmark's latitude, up to 32 minutes per week [42], which also affects PV generation. Thus, the daily persistence PV forecast will be used.

The reasoning for daily persistence being better for the spot prices and grid CO_2 intensity is similar; they are heavily dependent on solar and wind production in Denmark which is generally more steady from day to day than week to week. Due to the large renewable energy (RE) permeation in the Danish energy sector and their cheap levelized cost of energy, both the spot price and CO_2 intensity fall with increasing RE production and rise with decreasing RE production, where expensive and CO_2 emitting power plants are brought into operation.

The *Day-Ahead Spot Prices* aren't a forecast, but will be used since the hourly day-ahead prices are published at 13:00 CET every day, and the EMS can therefore access them in a real system, meaning the error in the price forecast is reduced to zero for a short enough optimization horizon. The expectation is that an optimization performed using the day-ahead spot prices will outperform an optimization based on persistence forecasted prices.

The *Day-Ahead CO_2 Prognosis* is a forecast (unlike the day-ahead spot prices) published at 15:00 CET every day and therefore has uncertainty associated with it. However, the forecast is more sophisticated than the naive persistence forecast, since it is based on the production schedules for all power plants in Denmark, which in turn are based on the day-ahead market [41]. Its higher accuracy is evident in Table 3.4, with a RMSE of 10.7 g-CO_2 / kWh versus 62.0 and 80.7 g-CO_2 / kWh for the daily and weekly persistence forecast, respectively. Thus, an optimization of CO_2 emissions done with this should outperform one done with the persistence forecast, and this will be used as the CO_2 forecast going forward.

3.6 Cases

With the distinction between a hybrid and double inverter system made, and with the battery control strategies and forecasts in place, the different cases are now presented. They are shown in Table 3.5.

Table 3.5: The different cases that will be modelled

Index	Control	Objective Function	Forecast
1	SCM	-	-
2	ToUA	-	-
3	Optimization	Cost	Persistence + Day-Ahead Spot Prices
4	Optimization	CO_2 (No Credit)	Persistence + Day-Ahead CO_2 Prognosis
5	Optimization	CO_2 (With Credit)	Persistence + Day-Ahead CO_2 Prognosis
6	Optimization	Cost	Oracle
7	Optimization	CO_2 (No Credit)	Oracle
8	Optimization	CO_2 (With Credit)	Oracle
9	Optimization	Multi-Objective	Persistence + Day-Ahead Spot Prices + Day-Ahead CO_2 Prognosis
10	Optimization	Multi-Objective	Oracle

Note that the first 8 cases are modelled for both inverter configurations. The multi-objective optimization is only modelled for the superior inverter configuration and with the superior CO_2 objective function due to the computational limitations of the project.

Oracle cases quantify the theoretical optimum for the different objective functions, and thus serve as benchmarks for the cases that are feasible to implement in a real system. An oracle case is defined by perfect forecasts of any relevant values infinitely far into the future, so that the ideal battery schedule can be calculated. After testing, it was found that optimizing for a period of 11 days at a time, corresponding to a optimization horizon of $n = 3168$ steps, was sufficient to approximate this behavior.

Adjusting horizon optimizations are run with a variable, or adjusting optimization horizon, hence the name. The optimizations using persistence PV and load forecasting, day-ahead spot prices and the day-ahead CO_2 prognosis are adjusting horizon optimizations. This is a consequence of data availability. In the case of the spot prices, they are published at 13:00, meaning at 13:00 one would know the prices until and including 23:00 the next day. This corresponds to an optimization horizon of 35 hours, or 420 steps. At 13:05 one would know the prices for the next 34 hours and 55 minutes, or 419 steps, and so on until 12:55 the next day where one knows the prices for the next 11 hours, which is 132 steps. The day-ahead CO_2 prognosis is published at 15:00 every day, so similarly one would know between 33 hours (396 steps) and 9 hours (108 steps) for the optimization. Thus, these cases also constitute the implementable versions of the optimization control strategies.

For the adjusting horizon cases, the optimization must be run for every timestep of the simulation, which is 210240 steps for 2 years of data at a 5-minute resolution (there are no leap years in the data). Thus, after implementing the optimal battery schedule at a timestep t, the optimization is re-run at the next timestep with the newest PV/load measurements and forecasts, and so forth. This is to ensure physical feasibility of the solutions. If the battery schedule from one optimization was implemented for the entire optimization horizon, it might violate the power balance in the system since the schedule depends on forecasted values. But the first step in the battery schedule will always satisfy the constraints, since the optimizer can be given the actual PV and load values for that timestep. The oracle cases do not need reoptimization at every timestep, since they have perfect knowledge of PV production and load, ensuring all constraints in the optimization problem will be respected at all timesteps. This makes for a much less computationally intensive task.

3.7 Evaluation Metrics

To properly evaluate the different cases, different metrics are derived. These are presented in the following sub-sections, and pertain to a control strategy's economic and environmental performance, along with the battery health.

3.7.1 Economic and Environmental Performance

Each case is evaluated on its economic and environmental performance. To do this, the electricity costs and CO_2 emissions of the different cases are calculated. The electricity cost for a case C is calculated by:

$$K^{C}_{Cost} = \sum_{i=1}^{L} (p_i^{\mathrm{b}} \lambda_i^{\mathrm{b}} - p_i^{\mathrm{s}} \lambda_i^{\mathrm{s}}) \Delta T \tag{3.4}$$

Where L is the length of the dataset, which is 210240 for the two-year period, and p_i^{b} and p_i^{s} is the power bought and sold at every timestep for the case. Similarly, the CO_2 emissions are calculated by:

$$K^C_{CO_2,NC} = \sum_{i=1}^{L} (p_i^{\mathrm{b}} \lambda_i^{\mathrm{CO_2}}) \Delta T \tag{3.5}$$

$$K^C_{CO_2,WC} = \sum_{i=1}^{L} (p_i^{\mathrm{b}} \lambda_i^{\mathrm{CO_2}} - p_i^{\mathrm{s}} \lambda_i^{\mathrm{CO_2}}) \Delta T \tag{3.6}$$

Where the notation $CO_{2,NC}$ refers to the no credit scenario and $CO_{2,WC}$ refers to the with credit scenario. Both CO_2 calculations are used because the CO_2 optimizations are done using two objective functions, each of which corresponds to one of the above calculations. Once the cost for a case is established, its economic benefit B^C is calculated as the difference between the energy costs under the baseline scenario of no battery (K^{Base}) and the energy costs with the battery:

$$B^C_{Cost} = K^{Base}_{Cost} - K^C_{Cost} \tag{3.7}$$

Similarly, the emissions benefit is then calculated according to:

$$B^C_{CO_{2,NC}} = K^{Base}_{CO_{2,NC}} - K^C_{CO_{2,NC}} \tag{3.8}$$

$$B^C_{CO_{2,WC}} = K^{Base}_{CO_{2,WC}} - K^C_{CO_{2,WC}} \tag{3.9}$$

The absolute benefits of the cases, which are in DKK and kg-CO_2, may also be expressed in relative terms by comparing with the theoretical maximum as obtained when using the oracle forecasts and appropriate objective function:

$$rB^C_{Cost} = \frac{B^C_{Cost}}{B^O_{Cost}} \tag{3.10}$$

$$rB^C_{CO_{2,NC}} = \frac{B^C_{CO_{2,NC}}}{B^O_{CO_{2,NC}}} \tag{3.11}$$

$$rB^C_{CO_{2,WC}} = \frac{B^C_{CO_{2,WC}}}{B^O_{CO_{2,WC}}} \tag{3.12}$$

To clarify, B^O_{Cost} refers to the cost benefit when using oracle cost optimization, $B^O_{CO_{2,NC}}$ refers to the CO_2 benefit of the oracle CO_2 no credit optimization calculated according the no credit metric, and $B^O_{CO_{2,WC}}$ refers to the CO_2 benefit of the oracle CO_2 with credit optimization calculated according to the with credit metric. This ensures that all benefits are normalized against the optimum value for each metric. The total relative benefit of a case can be calculated as the sum of the relative benefits for that case:

$$rB_{Total} = rB^{C}_{Cost} + rB^{C}_{CO_{2,NC}} + rB^{C}_{CO_{2,WC}} \tag{3.13}$$

The maximum rB_{Total} is then 3, by definition. If only one of the two CO_2 benefits is included (e.g. to weight cost and emissions equally, or if one of the CO_2 metrics is deemed unimportant), then the maximum achievable rB_{Total} is 2 and it is calculated as:

$$rB_{Total} = rB^{C}_{Cost} + rB^{C}_{CO_{2,NC}} \tag{3.14}$$

$$rB_{Total} = rB^{C}_{Cost} + rB^{C}_{CO_{2,WC}} \tag{3.15}$$

Note that environmental benefit, CO_2 benefit and emissions benefit are used interchangeably in this project.

3.7.2 Payback Period

Cases can also be evaluated on their payback period. The traditional (simple) payback period is defined as:

$$\text{Economic Payback Period} = \frac{\text{Cost of Investment}}{\text{Annual Cashflow}} \tag{3.16}$$

This will be referred to as the *Economic Payback Period*, since it is concerned with monetary costs and cashflows. Another payback period, the *Environmental Payback Period*, is defined according to:

$$\text{Environmental Payback Period} = \frac{\text{CO}_2 \text{ Footprint of Investment}}{\text{Annual CO}_2 \text{ Savings}} \tag{3.17}$$

The simple payback period ignores inflation, discount rates and hinges on the assumption that the annual benefit continues being the same in the future. Thus, it has its shortcomings, but is nonetheless a good indicator if an investment is worth it. Most importantly, it can be used to compare the different cases to each other, which is the point of its use in this project.

3.7.3 Battery Health

As mentioned previously, the number of cycles for the battery in each control strategy will be monitored, so the implications of different controls for the battery efficiency and lifetime can be discussed. The battery cycles for a control strategy are calculated according to:

$$\text{Cycles} = \frac{\text{kWh throughput}}{\text{2x nominal capacity}} = \frac{\sum_i^N (p_i^{\text{c}} + p_i^{\text{d}})\Delta T}{2 \cdot C_{bat}} \tag{3.18}$$

Where C_{bat} is the capacity of the battery. The average SOC in a control strategy is taken as the arithmetic mean of the SOC over the evaluation period:

$$s_{avg} = \frac{1}{N}\sum_{i}^{N} s_i \tag{3.19}$$

3.8 Practical Implementation

All modelling and data handling is done in Python version 3.9. Universal Coordinated Time (UTC) is used to avoid issues with daylight savings that may arise when working with time series in Central European Time (CET). The Python packages used are:

- **Numpy** - A library for numerical computing with support for large, multi-dimensional arrays and matrices, along with a collection of mathematical functions to operate on these arrays.
- **Pandas** - A data manipulation and analysis library providing data structures like DataFrames to work with structured data easily and efficiently.
- **Matplotlib** - A plotting library for creating static, interactive, and animated visualizations in Python.
- **Datetime** - A module in Python's standard library for working with dates and times.
- **Pytz** - A library for working with time zones, allowing accurate and cross-platform timezone calculations.
- **Math** - A module in Python's standard library providing mathematical functions.
- **CVXPY** - A library for defining and solving convex optimization problems in a natural and readable way.
- **Gurobi** - A solver for mathematical optimization, including linear programming, quadratic programming, and mixed-integer programming linear problems.

The parameters that are used in the modelling are:

- $\overline{p}_{inv} = 5$ kW
- $\overline{p}_{bat} = 7.675$ kW
- $\overline{s} = 8$ kWh
- $\underline{s} = 0$ kWh
- $s^0 = \frac{1}{2}\overline{s} = 4$ kWh
- $s^n = \frac{1}{2}\overline{s} = 4$ kWh
- $\eta_c = \eta_d = 0.95$

The upper limit on the SOC was chosen by rounding up the 7.7 kWh battery capacity, and the lower limit is set to 0 kWh, such that 8 kWh of battery capacity is available. In practice it is not advisable to fully discharge a battery since this can lead to capacity losses and stability issues [43], but this does not affect the results since battery degradation is not modelled and the upper and lower limits of the SOC do not matter for the control strategies, only their difference - it would be the same with $\overline{s} = 9$ kWh and $\underline{s} = 1$ kWh, for example. Of course, the available battery capacity is thus slightly higher in the model than in the real case, but since the goal is to compare battery strategies it does not matter. In any case, a sensitivity analysis of the battery capacity on the results is conducted, to show how they are affected.

The efficiencies, which are meant to represent both battery and inverter efficiency, were settled on as follows: the round-trip efficiency of the battery is at least 96% (Table 2.3). Going with the lower limit of 96%, and assuming that the charging and discharging efficiencies are the same, they are:

$$\eta'_c = \eta'_d = \sqrt{\eta_{\text{round-trip}}} = \sqrt{0.96} = 0.98$$

The inverter efficiency is dependent on power throughput, but the mean efficiency can be taken to be 97.44 % based on numerical integration of its efficiency curve [35]. Thus, the charging and discharging are taken to be:

$$\eta_c = \eta_d = \eta'_c \cdot \eta_{Inverter} = 0.95 \cdot 0.9744 \approx 0.95$$

4 Results and Findings

This section presents the results and findings of the investigation. The matter will be approached systematically, in an effort to comply with the project objective of providing recommendations for a residential prosumer. The section is therefore structured as follows:

First, the hybrid inverter configuration is compared to the double converter configuration. Only the superior configuration will be used in the remainder of the section, being taken as representative of both configurations. Second, the different control strategies will be compared. This includes finding the best optimization-based control strategy (excluding the multi-objective optimization), and the best heuristic control strategy. The third section will be brief battery health assessment for the different cases. Fourthly, a sensitivity analysis will be conducted to see how battery parameters affect the economic and environmental benefit of the system. Lastly, the multi-objective optimization problem will be compared against its two constituents.

The reason the multi-objective optimization is only included in the end is two-fold. Firstly, its objective function depends on whether exports are given a CO_2 credit or not. Secondly, the exact objective function is dependent on the value of k, i.e. the weight given to optimizing emissions over cost. Thus, investigating the multi-objective optimization is in itself an extensive task and therefore is only done for the best inverter configuration and best CO_2 objective function to limit the scope.

4.1 Prosumer Overview

This section presents an overview of the prosumer's energy production, consumption, cost and emissions over the evaluation period, to create an overview and facilitate comparison between the base case and the cases that are investigated. The quantities are shown in the table below.

Table 4.1: Overview of the energy, cost and CO_2 quantities of the prosumer in the 2-year period.

Quantities		
PV production	10055	kWh
Consumption	6162	kWh
Base cost	2074	DKK
Base emission[1]	402	kg-CO_2
Base emission[2]	-352	kg-CO_2

Evidently, the PV production in the period exceeds the consumption by quite a margin (it is 63%) higher, but the prosumer still has a net electricity cost of 2074 DKK since revenue from PV production was smaller than electricity costs. The CO_2 footprint of imported electricity is 402 kg, and drops to -352 kg if exported electricity is given a CO_2 credit.

[1]Calculated according to the CO_2 no credit method.
[2]Calculated according to the CO_2 with credit method.

4.2 Hybrid Vs. Double Inverter Configuration

In this section, the hybrid versus double configuration is compared across the strategies. The aim is strictly to ascertain which is better, before further results and analysis is conducted with a focus on control strategies. The modelling results (costs and CO_2 footprint) for the hybrid and double inverter configurations are shown in Tables A.1 and A.2 in the appendix. Below, the benefits for the different metrics are displayed for both configurations:

Table 4.2: The benefit of the different control strategies for the hybrid inverter configuration.

Index	Forecast	Control	B_{Cost} [DKK]	$B_{CO_{2,NC}}$ [kg-CO2]	$B_{CO_{2,WC}}$ [kg-CO2]
1	-	SCM	4047	250	-4
2	-	ToUA	4055	249	-5
3	Adjusting Horizon	Cost Optimization	5938	150	39
4		CO2 (No Credit) Optimization	3744	258	44
5		CO2 (With Credit) Optimization	-17792	-981	433
6	Oracle	Cost	6837	212	44
7		CO2 (No Credit)	4421	295	47
8		CO2 (With Credit)	-19625	-1066	535

Table 4.3: The benefit of the different control strategies for the double inverter configuration.

Index	Forecast	Control	B_{Cost} [DKK]	$B_{CO_{2,NC}}$ [kg-CO2]	$B_{CO_{2,WC}}$ [kg-CO2]
1	-	SCM	4048	250	-4
2	-	ToUA	4056	249	-5
3	Adjusting Horizon	Cost Optimization	5970	144	36
4		CO2 (No Credit) Optimization	3747	258	46
5		CO2 (With Credit) Optimization	-20509	-1108	551
6	Oracle	Cost	6873	208	44
7		CO2 (No Credit)	4422	296	48
8		CO2 (With Credit)	-23185	-1212	625

To better visualize the results and compare the effect of the inverter setup on each case, all cases are normalized against the double inverter result of that case. For example, the cost benefit under SCM with the hybrid inverter (4047 DKK) is normalized against the cost benefit under the double inverter (4048 DKK), and so forth for each case and type of benefit.

The exception is for negative benefits, which may arise in some control strategies. For example, the oracle CO_2 with credit optimization yields negative benefits for cost, -19625 DKK for the hybrid case and -23185 DKK for the double case. If the hybrid value is normalized against the double value, it will be less than 1, which implies it is outperformed by the double inverter setup. This is not the case; the hybrid setup has a less negative, i.e. 'less bad' cost benefit, and the normalized values should reflect this. In such cases, the calculation is reciprocated so that the double value is normalized against the hybrid value.

This will then reflect performance fairly, irrespective of whether the benefits are positive or negative. The scale is then consistent: if the normalized value is below 1, the double setup performs better; if it is above 1, the hybrid setup performs better.

This results in the following plot (with reciprocated normalizations shown with striped bars, i.e. where both configurations have negative benefits):

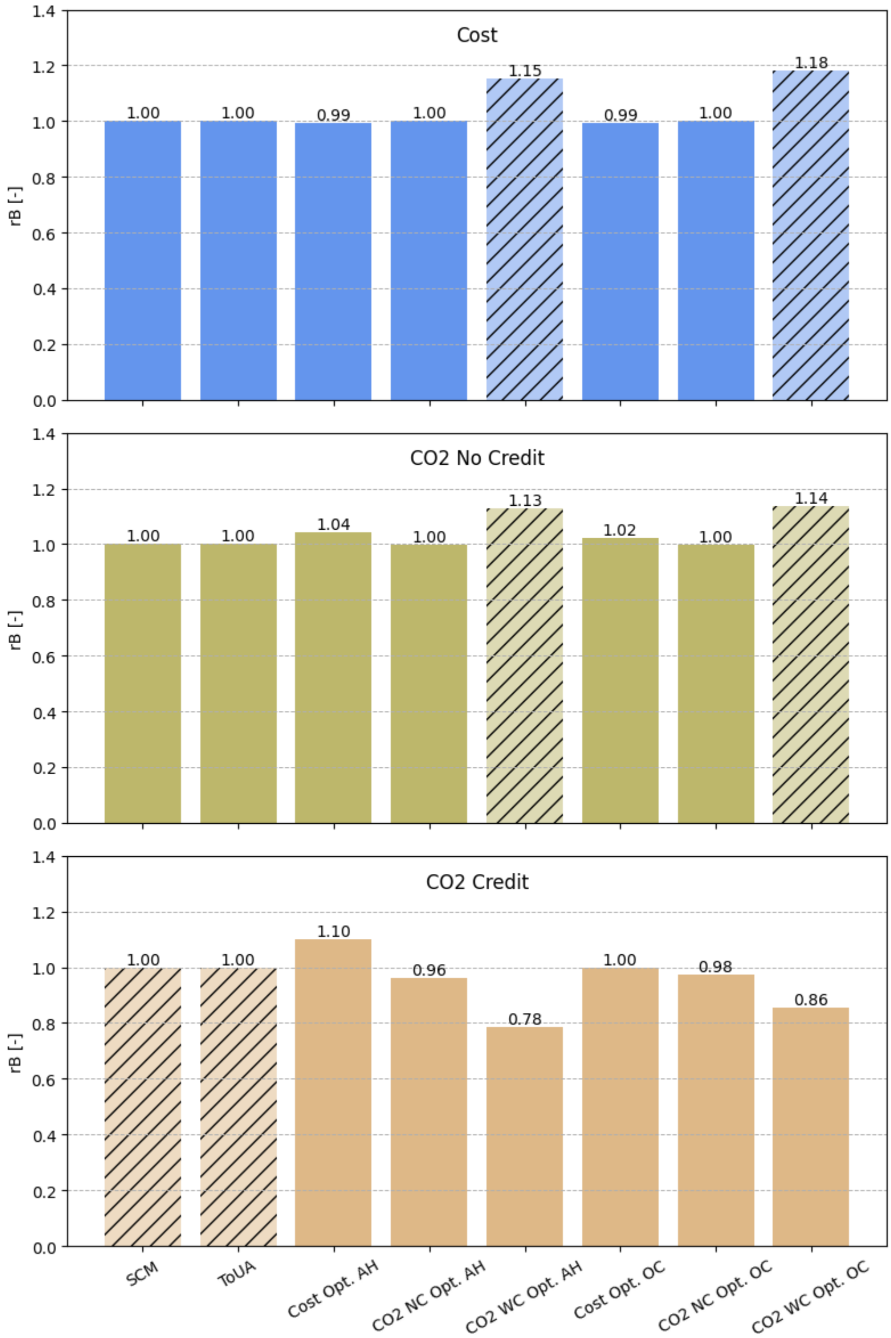

Figure 4.1: The benefit of the hybrid inverter normalized against the benefit of the double inverter, for each case and each type of benefit. *AH = Adjusting Horizon, OC = Oracle.*

It is evident that the benefit the double inverter brings is marginal or non-existent, depending on the case and metric. Inspecting the costs first, the double inverter setup barely outpeforms the hybrid setup in the majority of the cases, and does worse in both the adjusting horizon and oracle CO_2 with credit optimization. The hybrid inverter oracle cost case brings 99% of the benefit that the double inverter oracle cost case has in the 2 year evaluation period. In absolute numbers, the benefits are 6873 DKK and 6837 DKK. The double inverter setup thus has a maximum theoretical economic benefit of 36 DKK over two years.[3] The best attainable economic benefit is derived from comparing the adjusting horizon cost optimization for the two setups, where the double inverter brings a greater benefit of only 32 DKK over the two years. With an inverter of this type costing around 20000 DKK [44], the economic payback period for an extra inverter is:

$$\text{Economic Payback Period} = \frac{20000 \text{ DKK}}{16 \text{ DKK/year}} = 1250 \text{ years}$$

Such an investment can in no circumstances be justified from an economic standpoint. Even if the benefit of 36 DKK in the oracle case is used - which is not achievable in practice since it assumes perfect future knowledge - the payback time is 1111 years. This ignores inflation, discount rates and assumes that the double inverter will yield the same added benefit each year, but it is hard to conceive a situation in which the investment could be justified, unless PV production is constantly at a maximum such that the inverter is always occupied. In that case though, it would make more sense to acquire an inverter with a larger capacity than the PV module's power rating, thereby providing spare inverter capacity for the battery to discharge. In the case of the prosumer in this study, a 12 kW inverter will be sufficient to cover the PV and battery if they are both outputting at a maximum. This will be the preferred solution, since one larger inverter is cheaper than 2 smaller inverters. The price for a fitting inverter with 12 kW capacity is around 22000 DKK [45], which is 2000 DKK more than the 5 kW inverter the prosumer has (but made by a different company). With the benefits being so small though, it would also not make economic sense to have one larger inverter, despite it being half the cost of having two smaller inverters.

From the environmental perspective, the results are not much different. For the CO_2 no credit calculation, the hybrid inverter oracle CO_2 NC case yields essentially 100% of the benefit of the double inverter oracle CO_2 NC case. The exacts benefits are 295.34 kg-CO_2 saved versus 295.95 kg-CO_2 saved, corresponding to an improvement of 610 g-CO_2 over the 2 years for the double setup. This is the theoretical optimum[4]. The other strategies, including the adjusting horizon CO_2 NC optimization (which is optimized for this metric), do not show any improvement in the double inverter setup. The prosumer's inverter has a carbon footprint of approximately 320 kg-CO_2 (sourcing and manufacturing of components, production and transportation) [46]. This thus leads to a CO_2 payback period of:

[3]Ignoring cases with a negative cost benefit, since the battery cannot be economically justified for those cases and the hybrid vs. double inverter discussion therefore is irrelevant.

[4]Again, ignoring negative benefits for the same reason as in the cost discussion.

$$\text{Environmental Payback Period} = \frac{320 \text{ kg-CO}_2}{0.305 \text{ kg-CO}_2/\text{year}} = 1050 \text{ years}$$

Which is also not achievable in practice, since this was using the oracle case optimized for this metric. Using the CO_2 with credit calculation, the double inverter can yield a benefit of 625 kg-CO_2 versus 535 kg-CO_2 from the hybrid, which is an improvement of 90 kg-CO_2 over the 2 years. In that case, the environmental payback period for the extra inverter is:

$$\text{Environmental Payback Period} = \frac{320 \text{ kg-CO}_2}{45 \text{ kg-CO}_2/\text{year}} = 7 \text{ years}$$

Which is much better, but it builds on the prosumer receiving a carbon credit for exported electricity and this strategy also comes with awful economic performance.

On this basis, the double inverter configuration is clearly *not* a good investment by any metric, and will not be investigated further. In any case, the results between the two inverter configurations are so similar that the transferability of any findings should be very high.

4.3 Comparing the Control Strategies

In this section, the different cases will be compared (now only for the hybrid configuration). The benefits are calculated according to (3.7-3.9), and the relative benefits are calculated according to (3.10-3.12). The results are the following:

Table 4.4: The relative benefits of the different cases.

Case	Forecast	Control	rB_{Cost} [-]	$rB_{CO_{2,NC}}$ [-]	$rB_{CO_{2,WC}}$ [-]
1	-	SCM	0.59	0.85	-0.01
2	-	ToUA	0.59	0.84	-0.01
3	Adjusting Horizon	Cost Optimization	0.87	0.51	0.07
4		CO2 (No Credit) Optimization	0.55	0.87	0.08
5		CO2 (Credit) Optimization	-2.60	-3.32	0.81
6	Oracle	Cost	1	0.72	0.08
7		CO2 (No Credit)	0.65	1	0.09
8		CO2 (Credit)	-2.87	-3.61	1

As expected, the adjusting horizon optimization approach for a given metric is the case that has the highest relative benefit for that metric (other than the oracles themselves). Cost optimization achieves 87% of the theoretical cost optimum, CO_2 NC optimization achieves 87% of the theoretical CO_2 NC optimum, and CO_2 WC optimization achieves 81% of the theoretical CO_2 WC optimum. The results are plotted in Figures 4.2 and 4.3 to aid their interpretation.

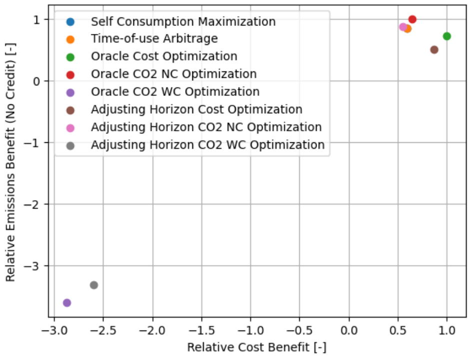

Figure 4.2: Emissions (no credit) benefit vs. cost benefit. SCM and ToUA have similar values and are therefore hard to distinguish.

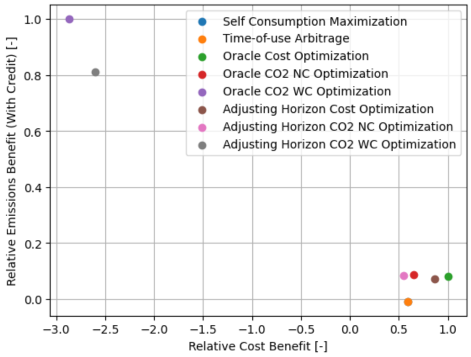

Figure 4.3: Emissions (with credit) benefit vs. cost benefit. The CO_2 with credit optimization results are *very* different from all the other cases.

4.3.1 The Rules-Based Controls

This subsection investigates which of the two-rules based control strategies is better for a prosumer. The two heuristics have an almost identical performance with one another, and they bring positive benefits for both cost and the CO_2 no credit metric, with very slight negative benefits on the CO_2 with credit metric. Despite their simplicity, a battery employing these strategies shows a clear benefit over not having a battery.

The time-of-use arbitrage strategy has a slightly greater economic benefit over the self-consumption maximization strategy (4055 DKK vs. 4047 DKK), and a slightly worse CO_2 no credit benefit (250 kg-CO_2 vs 249 kg-CO_2). This is not surprising considering the only difference between the two is that ToUA tries to take advantage of the typically high spot prices in the evening hours. With such a marginal economic benefit though, it cannot be recommended because the downside is much greater than the upside. If the trend with higher evening spot prices reverses, the battery will be discharging for no significant gain, and potentially need to recharge at a more expensive time because it 'wasted' its accumulated energy by discharging to the grid at low prices. This can be very costly. Thus, SCM is the preferred rules-based strategy. For ToUA to be more attractive, it could make use of the day-ahead spot prices and statistical techniques such as moving averages to allow it to discharge when prices are high (quantified according to some metric), rather than 'blindly' discharging in the evening hours based on historic trends. This however, is outside the scope of this project.

4.3.2 CO_2 No Credit vs. CO_2 With Credit Optimization

The goal of this subsection is to find out which of the two CO_2-optimized control strategies is superior. The optimizations performed with the CO_2 *with credit* objective function have extremely negative relative benefits for the cost and CO_2 no credit metrics. In practice, this means that a battery employing this strategy will be an economic burden on the prosumer, and it will also cause an increase in the CO_2 footprint of imported electricity. The battery may provide a service in that it helps alleviate the CO_2 footprint of the grid when it is high, but this alone cannot justify the investment of a battery. The Danish grid CO_2 intensity is better off being lowered by low-carbon electricity from large-scale solar and PV generation, although it can be considered a bonus if a prosumer helps work towards this. This grid-CO_2-alleviating battery strategy is not feasible for a residential prosumer - it is simply too much of an economic drain, and does not provide enough environmental value to offset this.

The explanation for this behavior is in the objective function. The power generated by the PV installation always has a lower CO_2 footprint than that of the grid, meaning the value of the objective function can always be decreased by exporting the power generated by the PV or the power stored in the battery. Thus, when the constraints allow for it, as much electricity as possible is exported, which in turn means the prosumer needs to import more power than otherwise necessary to meet demand. Due to the asymmetrical pricing between buying and selling prices, these back and forth imports and exports impose a huge cost on the prosumer, which is clearly seen in the results.

On the other hand, the CO_2 *no credit* optimization has positive relative benefits for every metric - including the CO_2 with credit metric. This means it always brings a benefit to the prosumer, no matter the metric it is judged by. It provides an economic benefit, whilst also reducing the CO_2 footprint of the prosumer's electricity imports *and* providing the service of exporting low-carbon electricity to the grid, thereby decreasing the CO_2 intensity of the grid electricity. This strategy forces the battery to minimize imports (weighted with the grid CO_2 intensity), since this is the only way to minimize the objective function. The battery behavior is thus similar to the rules-based strategies which try to avoid exchanges with the grid, and this can also be seen on the results in Figures 4.2 and 4.3. The fact that imports are minimized are also what results in the economic benefit despite the prices not appearing in the objective function. This key difference is evident below, where the imports and exports for the adjusting horizon cases are shown:

Table 4.5: The total and mean imports and exports across the 2-year evaluation period for the adjusting horizon CO_2 optimizations.

	Quantity [kWh]			
Objective	Total Import	Total Export	Mean Import	Mean Export
No CO2 Credit	1756	5308	0.0086	0.025
With CO2 Credit	14636	17234	0.070	0.082

The exports, and especially the imports, are clearly much larger when using the CO_2 *with credit* optimization, for the reasons explained above. To conclude, the CO_2 *with credit* optimization strategy is not a viable option for a residential prosumer, and the CO_2 *no credit* optimization approach is superior in every aspect. In the next section, the CO_2 *no credit* strategy will be discussed further, along with the cost optimization.

The CO_2 *with credit* optimization will not be investigated further except in the battery health section. The CO_2 *with credit* metric will also not be considered further.

4.3.3 Cost Optimization vs. CO_2 No Credit Optimization

In this subsection the cost and CO_2 *no credit* optimization strategies will be compared to each other and to SCM. With the CO_2 *with credit* optimization strategy discarded, the CO_2 *no credit* optimization will now just be referred to as CO_2 optimization for simplicity. A closer look at the results from Figure 4.2 is now possible:

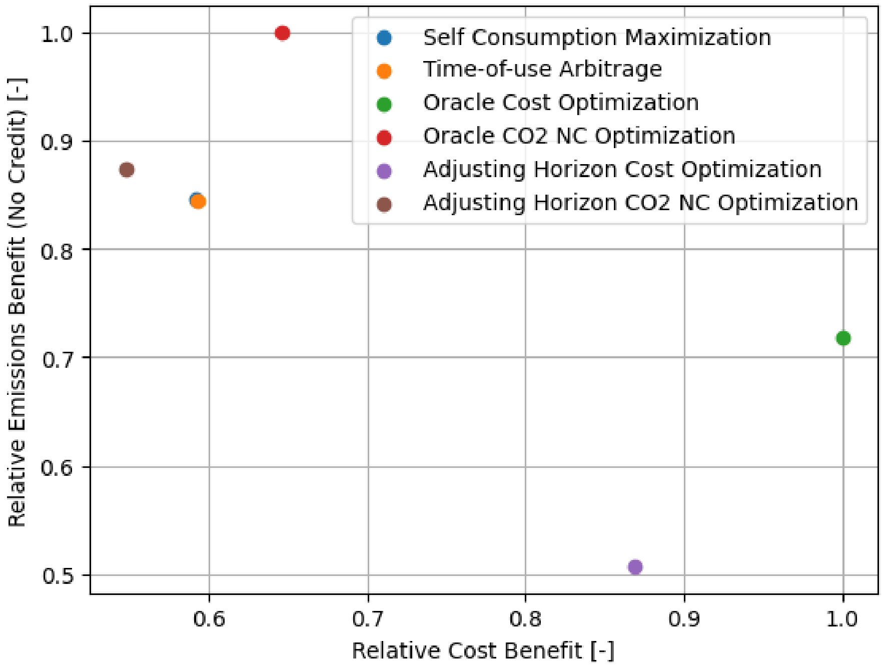

Figure 4.4: The relative benefits of the the control strategies for the different metrics. Note the blue SCM dot hidden behind ToUA. This plot is a zoomed-in version of Figure 4.2.

As with CO_2 optimization, cost optimization also performs positively for both the cost and emissions metrics.

The fact that both the cost and emissions optimization approach perform well for the metric they are not optimized for is no coincidence. For the CO_2 optimization, it is because it aims to minimize imports which brings an economic benefit due to the asymmetrical electricity prices as discussed earlier. For the cost optimization, it is because there is a tendency that lower spot prices and lower grid CO_2 intensity accompany one another. For the data used in this investigation, the Pearson correlation coefficient between the two is 0.54, which is a moderate positive correlation. The explanation for this lies in the fact that in the present day, electricity from wind turbines and solar PV is cheaper than other generation sources on a levelized cost basis, and it also has a lower CO_2 footprint than other generation sources. Thus, when wind and solar production is high in Denmark, spot prices and grid CO_2 intensity drop. This is seen in Figures 4.5 and 4.6.

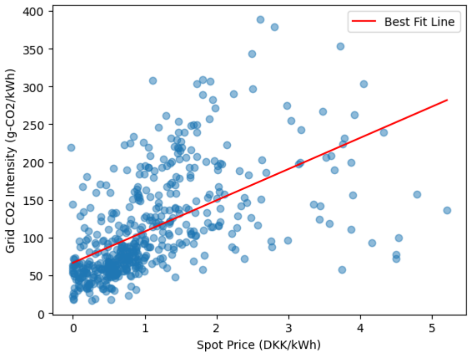

Figure 4.5: The grid CO_2 intensity vs. spot price for a random sample size of n = 500 in the evaluation period.

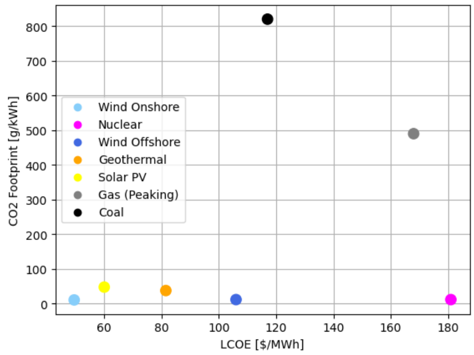

Figure 4.6: The levelized cost of energy and CO_2 footprint of selected energy sources. Data from [47] and [48].

It should be noted that spot prices are influenced by neighboring bidding zones and are a result of the balance between supply and demand, whereas the grid CO_2 emission is only a result of Danish electricity production. This why the correlation is only moderate. For example, if RE production is low in Denmark, fossil-fuel power plants will make up the majority of Danish production which means the grid CO_2 emission is high. A neighboring country like Sweden might have excess production from cheap hydropower though, which is then exported to Denmark, thereby lowering the spot price despite the high grid CO_2 intensity.

Comparing the oracle cases, the CO_2 optimization attains an relative cost benefit of 0.65 (and a relative emissions benefit of 1 per definition). The cost optimization attains a relative emissions benefit of 0.72 (with a relative cost benefit of 1). If the two metrics are given equal weight, this suggests that the cost optimization may be better; it has a total relative benefit of 1.72 versus the 1.65 of the CO_2 optimization, calculated according to Equation 3.14. In absolute terms, the cost benefit of cost optimization is 2416 DKK higher than CO_2 optimization (6837 DKK vs. 4421 DKK), and CO_2 optimization yields 83 kg-CO_2 more in saved emissions than cost optimization (295 kg-CO_2 vs. 212 kg-CO_2). These are the differences between the oracle forecasts for each optimization type.

For the adjusting horizon optimizations, which constitute the realistic forecasting cases, the findings are similar. The CO_2 optimization attains a relative cost benefit of 0.55 versus 0.87 for the cost optimization, or 3744 DKK versus 5938 DKK (out of 6837 DKK possible) in absolute terms. The cost optimization has a relative emissions benefit of 0.51 versus 0.87 for the CO_2 optimization, corresponding to 150 kg-CO−2 versus 258 kg-CO_2 saved (out of 295 kg-CO_2 possible). Thus, the economic benefit of cost optimization is 2194 DKK higher, and the emissions benefit of CO_2 optimization is 108 kg-CO_2 higher. The cost optimization has a total relative benefit of 1.38, and the CO_2 optimization achieves a slightly higher total relative benefit of 1.42, implying it may be a slightly better control strategy. Ultimately, this will depend on how the prosumer weights the emissons benefit versus the cost benefit. Most prosumers will probably be motivated by the economic upside of a battery, perhaps in tandem with the energy security it brings, with CO_2 savings being a secondary concern.

Comparing the two optimization cases with the rules-based cases, the total relative benefits are similar. SCM has a rB_{Cost} of 0.59 and a $rB_{CO_{2,NC}}$ of 0.85, for a total relative benefit of 1.44. ToUA, with its rB_{Cost} of 0.59 and $rB_{CO_{2,NC}}$ of 0.84 has a total relative benefit of 1.43. Both these are slightly higher than those of the adjusting horizon optimizations, meaning the rules-based cases outperform the optimization-based cases in this regard. The rules-based cases are rather fixed in their performance though, whereas the benefit of the optimization strategies can be increased if more accurate forecasts are provided.

4.3.4 Payback Periods

Going a step further, the simple economic and environmental payback periods for each case is calculated. The CO_2 WC optimization strategy is not considered since it brings negative costs benefits, meaning a battery implementing it could never pay itself back.

The cost of the prosumer's battery, including freight and installation is taken to be 50000 DKK (aggregate of [49, 50, 51]). The CO_2 footprint of the battery is taken as 560 kg-CO_2 [52]. The total payback time for a control strategy is the payback time of whichever one is larger since the cost and emissions savings work in parallel. The results are shown below:

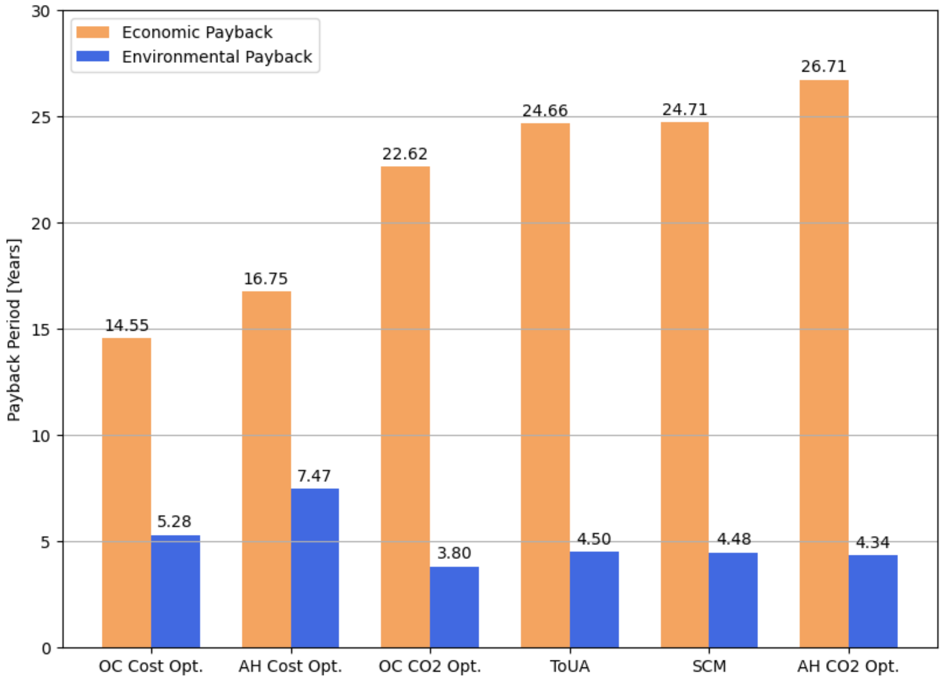

Figure 4.7: The payback periods for different cases. *AH = Adjusting Horizon, OC = Oracle.*

Several things can be concluded from this. Firstly, the economic payback time of the battery is much higher than the environmental payback time across the compared cases. The economic benefit the battery provides is highly dependent on the prosumer's consumption habits - if they were previously an active prosumer that sought to shift their consumption to the daylight hours when their PV installation was producing, a battery will not provide as great of a benefit as for a prosumer that had high consumption outside the PV generating hours. However, the battery provides an additional advantage in that it allows prosumers to be more flexible with their consumption, letting them consume their generated electricity outside of PV generation hours. This advantage, although hard to quantify, should not be underestimated. Ultimately though, its significance depends on how much a prosumer values having a more flexible power consumption. Also, with automatic load scheduling becoming more and more prevalent, the burding of shifting one's power consumption to PV-producing hours can be eased.

The theoretical payback time is 14.6 years, in the case of the oracle cost optimization, and the lowest attainable payback time is 16.8 years, which is for the adjusting horizon cost optimization. The cost optimization is clearly better than the CO_2 optimization, because a battery implementing this will have paid back both its economic and environmental cost 8 years before a battery implementing CO_2 optimization (for the oracle forecasts). With the adjusting horizon optimization, which uses actual forecasts and thus constitutes realistic cases, the cost optimization has a payback period that is almost 10 years less than that of the CO_2 optimization, which is a very significant difference. One difference between the two adjusting horizon optimizations are that for cost optimization, the EMS has access to the day-ahead spot prices which are fixed, meaning it has perfect price knowledge within its optimization horizon. In the case of the CO_2 optimization, it has access to the day-ahead CO_2 prognosis which, despite its accuracy, is still merely a forecast and thus has an error associated with it.

Cost optimization is also better than the rules-based strategies in terms of the payback period, but interestingly, the rules-based approaches have a shorter payback period than the (adjusting horizon) CO_2 optimization. Thus, based on the simple payback period of each strategy, one can conclude that cost optimization is best, followed by the rules-based cases, with the CO_2 optimization being worst.

4.4 Battery Health

In this section, the battery health for the cases (including CO_2 WC optimization) will briefly be assessed. The number of cycles in the 2-year evaluation period and the average SOC for the different cases are presented in Table 4.6.

Table 4.6: The number of cycles and average state of charge for the different cases (hybrid inverter configuration only).

Index	Forecast	Control	Cycles [-]	Average SOC [%]
1	-	SCM	781	49.3
2	-	ToUA	782	48.8
3	Adjusting Horizon	Cost Optimization	1072	45.8
4		CO2 (No Credit) Optimization	88	53.0
5		CO2 (With Credit) Optimization	3984	50.3
6	Oracle	Cost Optimization	908	44.7
7		CO2 (No Credit) Optimization	795	51.1
8		CO2 (With Credit) Optimization	4225	49.4

There are several things to notice. First, the oracle CO_2 WC optimization leads to a very high number of cycles in the 2-year period (3984 - 4225 cycles, depending on the forecast). This is once again due to the objective function, which incentivizes as many exports as possible and consequently also the discharging of the battery. The other optimization cases have a much lower number of cycles, but still more than the rules-based cases. This makes sense - the optimization approaches will use the battery more actively than the passive heuristics, which solely use the battery when a power surplus can be charged into it or a power deficit forces it to discharge. The average SOC is around 50% in all the cases, with the only exception being the cost optimization cases which are ~5% lower. The battery is rated for 6000 cycles or more [53], so if the lower limit of 6000 cycles is taken, an estimated lifetime under the different control strategies can be devised and plotted along with the payback times:

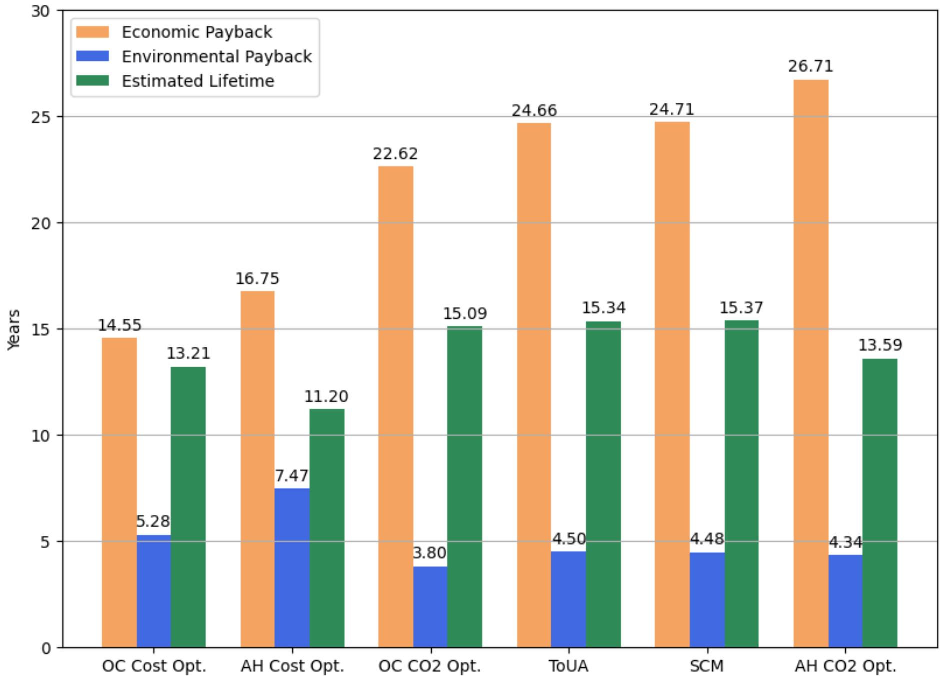

Figure 4.8: The payback periods for different cases. *AH = Adjusting Horizon, OC = Oracle.* CO_2 WC optimization is excluded from the plot since it has negative cost benefits.

It is evident that the estimated lifetime is less than the payback time across all cases, which essentially implies that the battery is not a good investment. This hinges on several assumptions however; firstly that the battery only lasts for 6000 cycles, and secondly that the benefit of the batter continues being the same year after year. It also ignores inflation and the discount rate. Nonetheless, it is very useful in comparing the different scenarios.

As expected, the oracle cost optimization performs best, making it through 91% of its payback period which can be taken as a benchmark. This is no surprise; it is optimized for cost, which is the hardest aspect of the investment in the battery to recoup, and it has perfect forecasting knowledge meaning it does not unnecessarily use the battery. Of the implementable strategies shown, the adjusting horizon cost optimization is the best, making it through 67% of its payback period. The rules-based cases make it through 62% of their payback period, and the adjusting horizon CO_2 optimization only makes it 51% through its payback period.

On this basis, it can be concluded that cost optimization is the best strategy for the residential prosumer to implement. It brings the greatest economic benefit, a sizeable environmental benefit, has the shortest payback period *and* the highest lifetime-to-payback ratio.

4.5 Sensitivity Analysis

In this section, a sensitivity analysis of the battery parameters on the economic and CO_2 footprint results will be conducted for selected cases. Self-consumption maximization is included and considered to be representative of the rules-based cases. Oracle cost and CO_2 optimization are included, since it is of interest to see how both the optimum cost and CO_2 NC benefits change and this can only be done full justice by including both types of optimization. Adjusting horizon cost optimization is also included since it is the best implementable control strategy.

The parameters that will be varied are the efficiency and the battery capacity (via the SOC upper limit, $\bar{s}$). The efficiency will be varied as per $\eta = \{0.90, 0.99\}$, and the capacity will be varied as per $\bar{s} = \{6, 10\}$ kWh. The default values were $\eta = 0.95$ and $\bar{s} = 8$ kWh. Note that η refers to both η_c and η_d as presented in the methodology section.

The sensitivity cases are assessed by their relative cost benefit rB_{cost} and their relative CO_2 benefit $rB_{CO_2,NC}$. The relative benefits are normalized against the benefits of the oracle cases. Concretely, the relative cost benefits are normalized against the cost benefit of the standard oracle cost optimization (6837 DKK), and the relative CO_2 benefits are normalized against the CO_2 benefits of the oracle CO_2 optimization (295 kg-CO_2). The results are then directly comparable to those in Figure 4.4. The results of the sensitivity analysis are shown in Tables A.5 and A.6 in the appendix, and also in Figures 4.9 and 4.10.

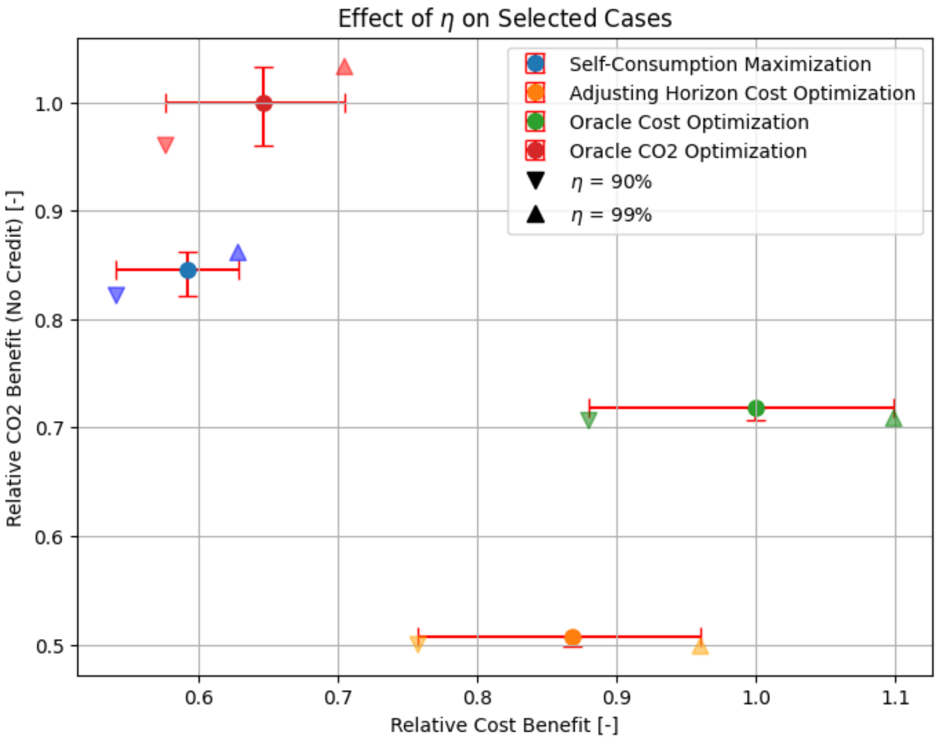

Figure 4.9: The effect of changing η on the relative cost and CO_2 benefits.

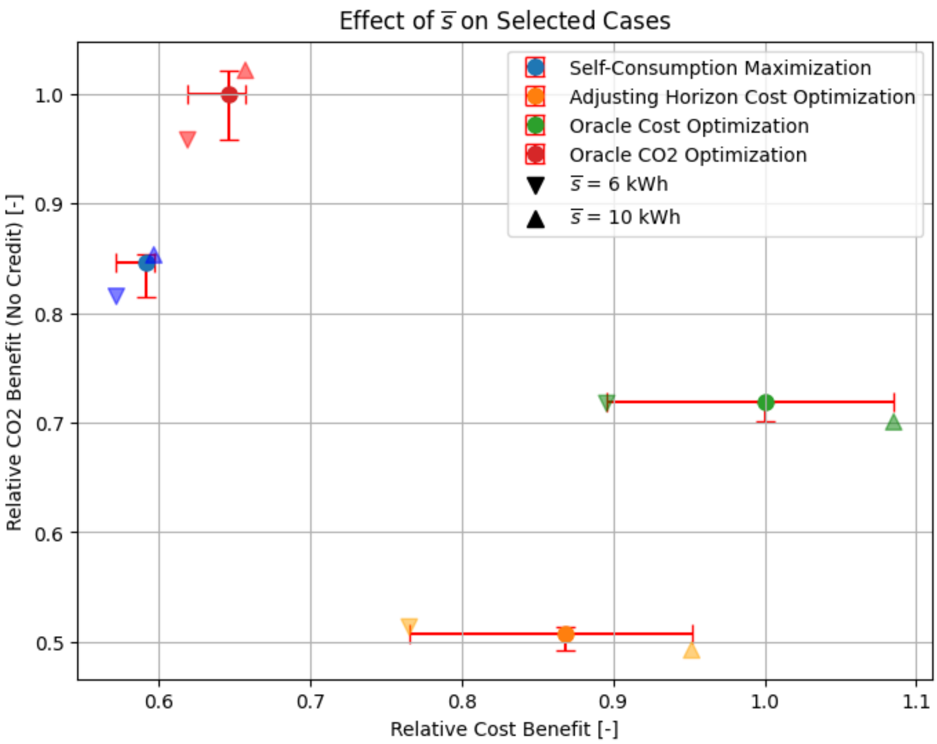

Figure 4.10: The effect of changing $\bar{s}$ on the relative cost and CO_2 benefits.

Across all the considered cases, increasing the system efficiency η increases the cost benefit, and decreasing the system efficiency decreases it. The same is true for the battery capacity $\bar{s}$ - increasing that also increases the cost benefit, and vice versa.

The effect of η is significant across all cases since it is a key parameter in all the control algorithms and optimization problems. The explanation for this is simple: if the efficiency decreases, the battery loses a higher share of energy every time it charges or discharges. This can for instance mean less PV generation is stored, more energy from the battery needs to be discharged to meet demand, or that less energy can be sold to the grid, all of which negatively impact profits.

The effect of $\bar{s}$ is also significant, but especially so for the optimization-based cases. This is because the maximum SOC is a key parameter in the optimization problems. Increasing it means the degree of arbitrage the battery can perform is greater - all else equal, the battery can simply store more power, meaning more PV generation can be self-consumed or low and high spot prices can be exploited for imports and exports.

In the rules-based cases, a higher battery capacity also means more energy can be stored in times of excess PV generation, which then means more energy is available during a power deficit. Due to the asymmetrical electricity prices, this is a benefit for the prosumer. However, $\bar{s}$ is not necessarily relevant to the battery control at every time step - it is only explicitly present when setting the limit on how much power can be charged to the battery during power surpluses and therefore when to begin exports. Since the battery is not always at full charge, $\bar{s}$ is not used at every time step the rules-based algorithms are run. This is why its effect is less prominent than that of η on cost benefits for the rules-based cases.

The effect of the parameters on $rB_{CO_{2,NC}}$ is not as great as on rB_{Cost}. It is greatest for the CO_2 optimization, which is natural seeing as it is optimized for this metric. Increasing η and $\bar{s}$ means the prosumer can store and use more self-generated power, and therefore needs to import less electricity, which is both expensive and CO_2 intensive in comparison. This is positive for both cost and CO_2 - hence the results. The explanation is the same for SCM, which also sees improvements in $rB_{CO_{2,NC}}$ with increasing η and $\bar{s}$. For the two cost optimizations however, increasing η and $\bar{s}$ does not result in an improved $rB_{CO_{2,NC}}$ - it actually decreases slightly. This can be attributed to the fact that these strategies have larger imports with an increased $\bar{s}$ (due to the larger magnitudes involved in arbitrage), which directly increases the prosumer's CO_2 footprint and therefore decreases $rB_{CO_{2,NC}}$. The decrease in $rB_{CO_{2,NC}}$ is not so drastic however, and this is because of the correlation between spot prices and grid CO_2 intensity.

Of the two investigated parameters, the efficiency η has the biggest effect. For cost optimization, a 1% change in efficiency resulted in a ~2.5% change in rB_{Cost}, whereas a 1% change in battery capacity resulted in a ~0.4% change for rB_{Cost} for the considered values. If a battery is to be included in a residential energy system, it should be chosen carefully, as its capacity and especially efficiency can significantly impact the system's profitability.

4.6 Multi-Objective Optimization

In this section, the multi-objective optimization approach will be compared to its constituents. The CO_2 no credit optimization has been shown to significantly outperform the CO_2 with credit optimization, hence the optimization problem that will be investigated is that of eq. 3.3a, i.e:

$$\min_{\mathbf{p}^{\mathrm{c}},\mathbf{p}^{\mathrm{d}},\mathbf{p}^{\mathrm{b}},\mathbf{p}^{\mathrm{s}},\mathbf{s},\boldsymbol{\delta},\boldsymbol{\sigma}} \quad \sum_{t\in\mathcal{T}} \left[(p_t^{\mathrm{b}} \lambda_t^{\mathrm{b}} - p_t^{\mathrm{s}} \lambda_t^{\mathrm{s}}) + k(p_t^{\mathrm{b}} \lambda_t^{\mathrm{CO_2}}) \right] \Delta T$$

With the constraints of eqs. 3.1b - 3.1g as in the other optimization problems. The multi-objective optimization is run for different values of k to determine how the emissions weighting influences the relative benefits. This is done for the hybrid inverter configuration and oracle forecast only, due to the limited computational resources available. The results for rB_{Cost} and $rB_{CO_{2,NC}}$ for selected values of k are shown together with the oracle cost and CO_2 optimization results in Figure 4.11. The modelling results (costs and CO_2 quantities) are shown in Table A.7.

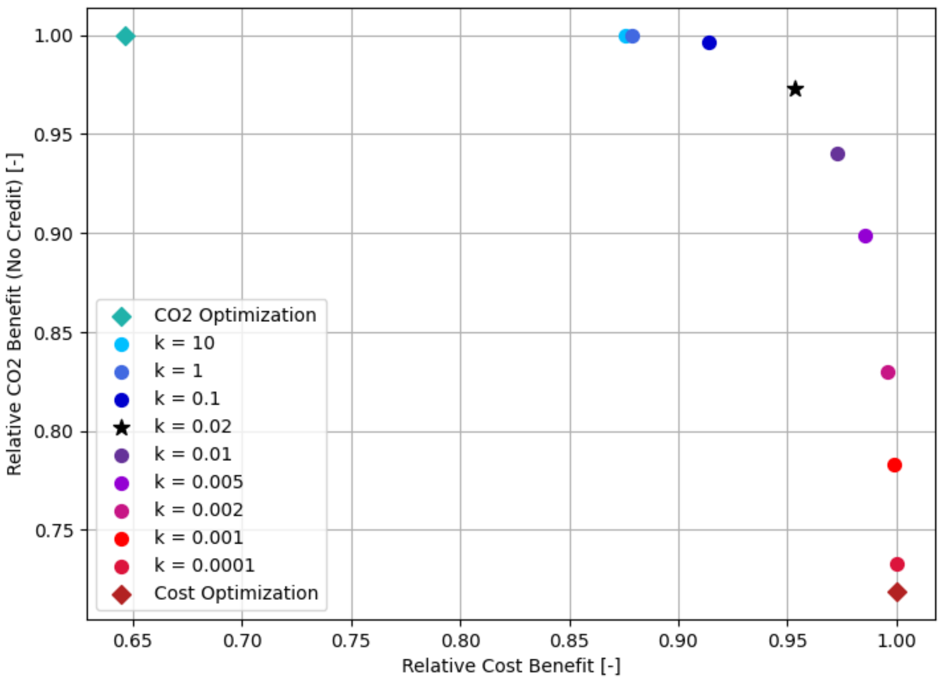

Figure 4.11: rB_{Cost} and $rB_{CO_{2,NC}}$ for the multi-objective optimization. *Oracle* only. $k = 0.02$ is depicted with a star marker because this value for k maximizes rB_{Total}.

Overall, the results of the multi-objective optimization are in between those of the cost and CO_2 optimization. The results converge to those of the cost optimization at values of $k << 1$. This makes sense, as cost optimization can be considered a special case of the hybrid optimization where $k = 0$.

On the other hand, the results for high values of k do not converge at those of the CO_2 optimization - they converge at $rB_{Cost} \approx 0.876$ and $rB_{CO_{2,NC}} \approx 1$. The convergence happens rapidly once $k > 1$, as can be seen in Figure 4.11. Larger values for k ($k = 100$ and $k = 1000$) were also tested, and the results were virtually the same as those of $k = 10$. The multi-objective optimization problem simply leads to a battery schedule that essentially reaches the same emissions reduction as in CO_2 optimization, but with a much greater profitability. To illustrate this: the emissions in CO_2 optimization are only $1.42 \cdot 10^{-14}$ kg-CO_2 less than in multi-objective optimization with $k = 100$. This is essentially just a rounding error, and means the multi-objective control achieves the same emissions reduction as the emissions control. The electricity costs are however 1566 DKK less with the multi-objective optimization, meaning it also achieves significant cost reductions over CO_2 optimization.

To verify that the multi-objective optimization does not converge at the CO_2 optimization results for high values of k, the optimization was also tested with k applied to the cost component instead of the emissions component, such that the weight of the cost could be controlled explicitly. A very small value $k = 0.00001$ still resulted in $rB_{Cost} = 0.876$ and $rB_{CO_{2,NC}} = 1$, the same result as a high k applied to the emissions component. Thus, it does not matter which component of the objective function the weight is applied to.

As previously established, the total relative benefits (sum of rB_{Cost} and $rB_{CO_{2,NC}}$) for oracle cost and oracle CO_2 optimization were 1.72 and 1.65, respectively. Of the considered values for k, every single one had a higher total relative benefit than 1.72, meaning the multi-objective optimization outperforms cost and CO_2 optimization by this metric. The highest total relative benefit was found to be 1.92 for $k = 0.02$, which is depicted with a star in Figure 4.11. This is quite close to an rB_{Total} of 2, i.e achieving the optimum cost and emission benefit.

This optimum value of $k = 0.02$ was run as an adjusting horizon optimization to see what benefit it would bring in a real system. It achieved a rB_{Cost} of 0.82 and $rB_{CO_{2,NC}}$ of 0.76, and thus had an rB_{Total} of 1.58. This is significantly better than both the adjusting horizon cost optimization ($rB_{Cost} = 0.87$, $rB_{CO_{2,NC}} = 0.51$, $rB_{Total} = 1.38$) and adjusting horizon CO_2 optimization ($rB_{Cost} = 0.55$, $rB_{CO_{2,NC}} = 0.87$, $rB_{Total} = 1.42$). Multi-objective optimization clearly has the potential to achieve sizeable reductions in both the prosumer's electricity costs and CO_2 footprint, with the added advantage of the prosumer being able to specify the weighting between the two.

Despite the higher total relative benefit, multi-objective optimization can not be recommended over cost optimization, simply because the monetary cost of the battery is hardest to recoup and it should therefore be the only focus of a control strategy - the emissions benefit is still significant when cost is the optimization objective.

5 Discussion

In this section, the findings from the previous section are discussed in a broader context.

5.1 Transferability

In this project, it was found that cost optimization also brought about a reduction to the household CO_2 footprint, and that CO_2 optimization also brought about a reduction in household electricity costs. This is largely due to the correlation between low spot prices and low grid CO_2 intensity in Denmark. In a country with a different energy mix, the correlation may be weaker or even reversed, and it is not sure that optimizing a battery schedule for one metric will also benefit the other.

In any case, the biggest effect on the battery benefit is the prosumer themself. If they are active prosumers that align consumption with PV production, then the benefit the battery brings them will not be as great as in the case of a passive prosumer that does not make an effort to use their self-generated energy. This goes both for both the cost and emissions metrics. The authors in Ref. [24] demonstrated this for costs by considering two prosumers with different consumption habits.

The analysis conducted in this project should thus be carried out for other load profiles and for different countries to substantiate the findings.

5.2 Modelling Assumptions

The assumption of a constant battery capacity in the modelling, i.e. no degradation has likely *not* impacted the model results significantly. The investigation is carried out in a two-year period, and with the number of cycles seen (except in the CO_2 WC optimization), battery capacity degradation is not likely to impact the cost and CO_2 footprint results. The effect of decreasing battery capacity was also investigated in the sensitivity analysis, and a relatively large degradation is needed before results are significantly impacted.

However, the payback period results may be affected by this assumption. The annual benefit in future years for a case is projected to be the same as the annual benefit from the two years which the modelling was done on. This gives a disproportionate advantage to the optimization-based cases over the rules-based cases. The optimization cases experience more annual cycles and their future benefits should thus be lowered to a greater degree in later years than the rules-based cases, if this was accounted for. The payback periods of the optimization cases would then increase more than the payback periods of the rules-based cases. Nonetheless, cost optimization has a payback period that is so much lower that it would in all likelihood still be preferred over a rules-based control.

The results were much more sensitive to system efficiency than battery capacity, as was also shown in the sensitivity analysis. A constant efficiency was assumed in this investigation, but the inverter efficiency is dependent on power throughput, and battery efficiency is dependent on power throughput and SOC. Battery efficiency would be hard to model, but the inverter efficiency can relatively easily be incorporated by making use of its efficiency curve. Having not just non-constant, but non-linear efficiencies would however increase the complexity of the optimization problems. It is uncertain whether the optimal battery schedule would change, and an investigation of that would be interesting. If the schedule does not change by much, it is not worth the extra computational complexity, which the hardware of a real EMS might not be able to handle.

5.3 Implementation in Real Systems

The methodology used in this project can be implemented into a real EMS. The rules-based heuristics are already implemented in real batteries, and the optimization based approaches can be too.

The computational demands of the optimization based approaches is not high, and they rely on simple persistence forecasts and the publicly available day-ahead spot prices and/or CO_2 prognosis. Both the optimization algorithms and the external data are free. The control strategies presented in this project cost can thus be considered market ready. If implemented in other countries, the adjusting horizon optimization will have to be modified according to the availability of spot prices in that country (and grid CO_2 intensity if that is used).

6 Conclusion

This project has investigated the benefit of PV-battery systems across cases categorized by inverter configuration, battery control strategy and forecast type. The cases were evaluated in a 2-year period (1-1-2022 to 31-12-2023) based on their economic and emissions (CO_2) benefit. The basis for the project was prosumer data (load and PV generation) from a real household in Roskilde, Denmark. Grid CO_2 intensity data and spot prices were also used.

Energy costs for a case were calculated as the cost of electricity imports minus the revenue from exports. For the CO_2 footprint, two calculations were considered. In the first calculation the prosumer's CO_2 footprint was solely based on imports, and in the second the imports were offset by the prosumer's exports since they were considered to give a carbon credit (just like the prosumer receives a monetary credit when exporting electricity). The name given to these two metrics were CO_2 *no credit* and CO_2 *with credit*, respectively. To quantify the benefit of the battery in a given case, the costs and CO_2 footprints were compared to the cost and CO_2 footprints of the prosumer without a battery. Of the considered cases, some were so-called 'oracle' cases that were considered to quantify the theoretical optimum of the different benefits.

A hybrid inverter setup and a double inverter configuration were investigated, which place different restrictions on the battery's discharge power. In the hybrid inverter setup, the battery's discharge power was limited to the inverter capacity (5 kW) minus the PV production, and in the double inverter configuration, the only limit was the battery's own power rating (7.675 kW) since an inverter dimensioned for the battery was assumed. It was shown that across all battery control strategies and forecasts, the benefit of a double inverter setup was either marginal or non-existent. The maximum theoretical benefit of the double inverter was 36 DKK over the two years. With the price of a second inverter being in the range 20000-35000 DKK, it is not a good investment. Having one large 12 kW inverter instead of the 5 kW inverter would also not be worth it, since the extra price of a larger inverter is likewise not recouped by the increased cost benefit. The double inverter setup also only yielded a 610 g-CO_2 reduction in the prosumer's CO_2 footprint over the evaluation period when optimized for emissions. With the CO_2 footprint of an inverter being 320 kg, the double inverter configuration does also not recoup this 'cost' within a reasonable timeframe. Investing in a second inverter - or a larger one - can not be recommended by any metric.

The different battery control strategies were all compared based on the economic and emissions performance metrics. The rules-based approaches performed well in all aspects considering their simplicity. SCM and ToUA achieved both achieved relative cost benefits of 0.59, and relative CO_2 NC benefits of 0.85 and 0.84 respectively. ToUA had a slightly higher economic benefit than SCM - 8 DKK in the evaluation period - but it is not advisable to implement it over SCM because it relies on the trend that spot prices are higher in the evening than otherwise. If this trend reverses, or even just tapers off, the small benefit that ToUA brings will quickly disappear and the battery's profitability may be eroded.

Optimization using the CO_2 *no credit* objective function far outperformed the CO_2 *with credit* optimization. The CO_2 WC optimization yielded significant *negative* benefits for cost and CO_2 NC. The prosumer's electricity costs increased from 2074 DKK in the evaluation period to 19866 DKK when the CO_2 WC optimization was implemented with the adjusting horizon forecast, and emissions from imports increased from 402 kg-CO_2 to 1384 kg-CO_2. Emissions when considering the CO_2 export credit however dropped from -352 kg-CO_2 in the base case to -785 kg-CO_2, meaning the battery decreased the CO_2 footprint of the grid by 433 kg.

On the other hand, the CO_2 NC optimization achieved positive benefits across all three metrics. It decreased the prosumer's electricity costs to -1670 DKK, meaning a profit of 1670 DKK was made selling excess electricity, and emissions from imports decreased to 144 kg-CO_2. Emissions when considering the CO_2 export credit also dropped, to -396 kg-CO_2. The cost optimization also boasted positive metrics, achieving a profit of 3864 DKK and emissions of 253 kg-CO_2 (-391 kg-CO_2 when considering the CO_2 export credit).

The optimization approaches led to a greater number of cycles in the battery than the rules-based heuristics. Thus, an optimization control strategy will wear down the battery faster, but as shown in Figure 4.8, the trade-off between profitability and lifetime is worth it.

Overall, the battery's economic payback time is much greater than its payback time (see Figure 4.7), suggesting the need to prioritize costs over emissions in a battery control strategy.

A multi-objective optimization control was investigated, where the battery schedule was optimized for both cost and emissions. Different weightings between the cost and emissions were considered, and it was shown that the total relative benefit of the system could be increased significantly if an appropriate weighting was applied. A theoretical rB_{Total} of 1.93 was achieved for $k = 0.02$, versus the theoretical $rB_{Total} = 1.72$ for cost optimization and theoretical $rB_{Total} = 1.65$ for CO_2 optimization. Nonetheless, cost optimization is still recommended as the control strategy for a residential prosumer since recouping the monetary cost of a battery takes much longer than recouping its CO_2 footprint. However, it will ultimately be up to a prosumer themself to decide what balance between profitability and emissions reductions is right for them.

Battery efficiency has a significant impact on the profitability of the system. For the cost optimization approach, a 1% change in efficiency corresponded to a more than 2% change in the economic benefit of the system. A 1% change in battery capacity corresponded to a change of approximately 0.4% in the economic benefit, so it was less impactful. For the rules-based heuristics, the impact of battery capacity was even less significant than for the cost optimization, but the efficiency had a large impact on results. Both the efficiency and the battery capacity did not impact emissions reductions as much as they did costs.

6.1 Further Work

Future work can be classified into two categories: 1) improve on the methodology employed in this study, and 2) expand the investigation.

Improvements to the methodology include:

- Investigate the effects of a more realistic (non-linear) battery model. This includes accounting for the degradation of battery capacity and efficiency throughout time, and non-constant efficiencies for different charging/discharging powers. Combined with this, the non-constant efficiency of the inverter should also be modelled, which can be done using the curves provided by the manufacturer.
- Investigate the benefit of a PV-battery system for other prosumer load profiles, since the benefit of a battery is highly dependent on consumption habits.

The scope of the investigation can also expanded by:

- Investigating the profitability and environmental footprint of other residential energy systems, such as PV-electric vehicle setups.

A Appendix

A.1 Model Results

Table A.1: Cost and CO_2 quantities for the hybrid inverter cases.

Case	Forecast	Control	Cost	CO_2 (No Credit)	CO_2 (Credit)
1	-	SCM	-1973	153	-348
2	-	ToUA	-1981	153	-347
3	Adjusting Horizon	Cost Optimization	-3864	253	-391
4		CO2 (No Credit) Optimization	-1670	144	-396
5		CO2 (Credit) Optimization	19866	1384	-785
6	Oracle	Cost	-4763	190	-396
7		CO2 (No Credit)	-2347	107	-399
8		CO2 (Credit)	21699	1468	-887

Table A.2: Cost and CO_2 quantities for the double inverter cases.

Index	Forecast	Control	Cost	CO_2 (No Credit)	CO_2 (Credit)
1	-	SCM	-1974	153	-348
2	-	ToUA	-1982	153	-347
3	Adjusting Horizon	Cost Optimization	-3877	253	-389
4		CO2 (No Credit) Optimization	-1657	145	-397
5		CO2 (Credit) Optimization	22583	1510	-904
6	Oracle	Cost	-4800	195	-396
7		CO2 (No Credit)	-2348	106	-400
8		CO2 (Credit)	25259	1615	-977

A.2 Payback Periods & Estimated Lifetimes

Table A.3: The economic and environmental payback times of the cases.

Case	Economic Payback Time [Years]	Environmental Payback Time [Years]
SCM	24.7	4.5
ToUA	24.7	4.5
Adjusting Horizon Cost	16.8	7.5
Adjusting Horizon CO2	26.7	4.3
Oracle Cost	14.6	5.3
Oracle CO2	22.6	3.8

Table A.4: The estimated lifetime of the battery for the different cases (hybrid inverter configuration only).

Index	Forecast	Control	Estimated Lifetime [Years]
1	-	SCM	15.4
2	-	ToUA	15.3
3	Adjusting Horizon	Cost Optimization	13.2
4		CO2 (No Credit) Optimization	15.1
5		CO2 (With Credit) Optimization	2.8
6	Oracle	Cost Optimization	11.2
7		CO2 (No Credit) Optimization	13.6
8		CO2 (With Credit) Optimization	3.0

A.3 Sensitivity Results

Table A.5: The effect of changing battery efficiency on the the relative benefits for selected cases.

Case	rB_{Cost}, $\eta = \{0.90, 0.99\}$	$rB_{CO_{2,NC}}$, $\eta = \{0.90, 0.99\}$
SCM	{0.541, 0.623}	{0.822, 0.862}
Adjusting Horizon Cost	{0.757, 0.960}	{0.500, 0.499}
Oracle Cost	{0.880, 1.099}	{0.706, 0.709}
Oracle CO2	{0.576, 0.705}	{0.960, 1.033}

Table A.6: The effect of changing battery capacity on the the relative benefits for selected cases.

Case	rB_{Cost}, $\bar{s} = \{6, 10\}$	$rB_{CO_{2,NC}}$, $\bar{s} = \{6, 10\}$
SCM	{0.572, 0.597}	{0.815, 0.853}
Adjusting Horizon Cost	{0.766, 0.952}	{0.514, 0.493}
Oracle Cost	{0.896, 1.086}	{0.718, 0.701}
Oracle CO2	{0.619, 0.657}	{0.958, 1.021}

A.4 Multi-Objective Optimization Results

Table A.7: The cost and CO_2 quantities for different values of k in the multi-objective optimization.

Weight k	Cost	CO_2 (No Credit)
10	3913.82	107.07
1	3935.47	107.08
0.1	4175.3	108.18
0.02	4495.94	115.07
0.01	4576.93	124.64
0.005	4665.90	136.91
0.002	4735.18	157.35
0.001	4755.25	171.26
0.0001	4762.89	186.01

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