Mikal-André Tvedt

Optimal Operation of Flexible Assets in a Residential Energy System

A Rolling Horizon Approach

Master's thesis in Energy and Environmental Engineering
Supervisor: Magnus Korpås
Co-supervisor: Kasper Emil Thorvaldsen
June 2022

Master's thesis

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Abstract

In recent years, solutions for electricity demand flexibility have become available for residential households. Flexible assets paired with incentive based demand response schemes can generate long term value for households.

This thesis presents an optimization model and algorithm for the optimal control of flexible assets using a rolling horizon approach. This approach is based on the cost minimization of a prediction horizon for each iteration. A Battery energy storage system, (BESS), Electric vehicle (EV) with Vehicle to home (V2H) capability, as well as Domestic hot water (DHW) were examined. The optimization model was applied to a case study and the assets were simulated together with an inflexible household load and input from a Photovoltaic system (PV). To capture the long-term value of the flexible asset operation, each month of 2021 was simulated under Real time prices (RTP), Time of Use (TOU) and Capacity Subscription (CS) pricing schemes. Under this approach, use of BESS was found to reduce yearly costs with 2% compared to a reference case, and flexible DHW provided up to 2.55% yearly cost reduction. Smart charging of the EV yielded a reduction of 5.7%, and 6.1% if bidirectional V2H charging was applied. Some months yielded lower cost savings with V2H enabled compared to ordinary smart charging. With the applied charge/discharge efficiency, high price variations are required in order for V2H to be profitable. In the case where all assets were present, yearly cost reductions were 7.93%. Although the grid tariff cost were reduced, a CS scheme with 5 kWh/h load limit appeared to limit the flexibility potential of flexible assets, as large loads were penalized regardless of the time of use.

Sammendrag

I nyere tid har løsninger for sluttbrukerfleksibilitet i etterspørselen etter strøm blitt tilgjengelige for private holdninger. Sammen med incentivordninger kan fleksible enheter generere langsiktig verdi for husholdningene.

Denne oppgaven presenterer en optimaliseringsmodell og algoritme for optimal kontroll av fleksible enheter under en rullende horisont. Denne tilnærmingen er basert på minimering av kostnader over en prediksjonshorisont som oppdateres for hver iterasjon. Et batterisystem (BESS), elektrisk kjøretøy (EV) med mulighet for toveis lading (V2H), samt fleksibelt varmtvann (DHW) ble undersøkt i denne oppgaven. Modellen ble brukt på et casestudie der enhetene ble simulert i operasjon sammen med en ufleksibel last og solkraft (PV). For å estimere den langsiktige verdien av de fleksible enhetene ble hver måned i 2021 simulert under sanntids strømpriser (RTP) og nettleie bestående av en kombinasjon av brukstid (TOU) og abonnert effekt (CS). Under denne tilnærmingen ble det funnet at BESS reduserer årlige kostnader med 2% sammenlignet med et referansecase, og fleksibelt DHW reduserte årlige kostnader med opp til 2,55%. Smartlading av EV ga 5,7%, og 6,1% hvis toveis V2H-lading ble brukt. Med den bruke ladeeffektiviteten kreves det høye prisvariasjoner for at V2H skal være lønnsomt. Som følge gav noen måneder lavere kostnadsbesparelser når V2H var aktivert sammenlignet med vanlig smartlading. I tilfellet der alle enhetene var simulert i samtidig operasjon, var årlige kostnadsreduksjoner 7,93%. Selv om nettleiekostnaden ble redusert, konkluderes det med at en CS-ordning med 5 kWh/t lastgrense virker begrensende for fleksibilitetspotensialet til fleksible enheter, da store laster ble straffet uavhengig av brukstidspunkt.

Preface

This work concludes my final year at the Norwegian University of Science and Technology. I am happy to have had the opportunity to study in Trondheim, and I am grateful for all the friends and experiences I gained along the way. I thank Kasper Emil Thorvaldsen and Magnus Korpås for valuable guidance in formulating and implementing the optimization model, results interpretation and for motivation throughout the semester. I would also like to thank my friends and family for their encouragement and support.

Mikal-André Tvedt
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Abbreviations

SOC	State of charge
DSO	Distribution system operator
TSO	Transmission system operator
NVE	The Norwegian Water Resources and Energy Directorate
PV	Photovoltaic
EV	Electric vehicle
VTG	Vehicle to grid
VTH	Vehicle to house
DHW	Domestic hot water
EWH	Electric water heater
HL	Household load
TOU	Time of use
CS	Capacity subscription
CH	Control horizon
PH	Prediction horizon
SH	Scheduling horizon
BESS	Battery energy storage system

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1 Introduction

1.1 Motivation

The Norwegian power system will experience increased production and power demand in the next two decades [1], attributed to the transition of the industrial and personal transportation sector to battery electric vehicles and the electrification of the offshore industries. The increase in production capacity is in large part due to intermittent sources such as solar and wind. Increased penetration of intermittent sources will cause increased fluctuations in electricity prices, both daily, seasonally and yearly. In addition, increasing CO_2 taxes and fuel prices will affect the electricity prices. In periods of low solar and wind production, the price of gas will determine the electricity price [1].

In order to meet the increasing fluctuations in prices, NVE expects domestic end-users to implement flexibility solutions in order to balance their demand on the power grid. Flexibility assets such as batteries can shift end-user load on the grid away from the expensive power peaks to other hours of the day [1].

In addition to pure flexibility assets like batteries, other assets can contribute to end-user flexibility by having their loads managed in an optimal manner. Such units may include battery energy management systems (BESS) electric vehicles (EV), and domestic hot water (DHW). Operation of these assets can play a key role in reducing the financial burden of increased prices placed on the end-user. However, to generate value in the long-term, these assets must be operated in a cost-optimal manner. Electricity prices and grid tariffs determine the total cost of electricity use, and the optimality of operation is subject to these price signals.

1.2 Objective

The main objective of this thesis is to develop an optimization algorithm using a rolling horizon approach, with the goal of optimal operation of flexible assets in conjunction with inflexible household load. The flexible assets to be examined are BESS, EV, EV-V2H and DHW, supplemented by a PV system. The algorithm will be applied to a case household to investigate cost optimality and the long-term value of said flexible assets.

1.2.1 Approach

The optimization model and algorithm will be developed in the programming language Python 3.8 using the Pyomo optimization package. Rolling horizon methodology will be used as framework for the algorithm. The assets will be simulated both in individual and simultaneous operation for each moth of 2021. Each asset configuration will be modeled as a linear program, and each day will be solved separately as an iteration of the algorithm, using the variable inputs gathered from the previous iteration. The strategy will be applied to a hypothetical case study in the Norwegian price zone NO5 with obtained household load data, PV data and prices.

1.2.2 Contributions

The contributions of this thesis are:

- Development of a rolling horizon algorithm and optimization model for operation of flexible assets in conjunction with an inflexible household demand load, using long-term electricity price signals and grid tariffs.
- Long-term value of operation of BESS, DHW, EV, and EV-V2H under the simulated conditions, as well as interpretations of the benefits of these assets.

1.2.3 Scope and delimitations

This thesis will only consider the cost of operation of the simulated flexible assets. The total investment cost of such a system will not be considered. Degradation and temperature effects on the batteries are considered to be negligible, as the operational period of the model is relatively short. Payback period, net present value or depreciation calculations will not be performed.

1.3 Structure

This paper is divided into 6 chapters. In Chapter 2, the framework of the paper will be presented. This includes the necessary background information on the Norwegian power market and the relevant regulatory framework, as well as a literature review on the operation of flexible assets. Chapter 3 presents the methodology behind the optimization approach, as well as the formulation of the algorithm and the optimization model. Chapter 4 contains a description of the case study, and in Chapter 5 the results are presented and discussed. Finally, Chapter 6 contains the conclusion. The script implementation is presented in Appendix A.

2 | Framework

This chapter introduces the relevant framework for the current power market functions and pricing mechanisms. Additionally, flexible assets are presented along with the relevant background material and literature review on the optimal operation of such assets. The assets examined in this thesis are BESS, DHW, EV and EV-V2H.

The content in Section 2.1, 2.2, and 2.3 were originally part of the preceding project thesis as presented in [2]. The content has been reviewed and modified in accordance with the objectives of this Masters thesis.

2.1 The Norwegian power system and market

The Norwegian power market is a liberalized market that is subject to the market forces. Since the restructuring of the Norwegian and Nordic power market following the 1990 Energy Act, electricity has been regarded as a commodity which price is determined by supply and demand. The reason for the restructuring was to create a more efficient system based on market forces. This way, competition would incentivize cost savings and decentivize unprofitable and oversized investments. The price of electricity was to be determined by the market rather than political institutions [3]. The market participants are presented in this section.

2.1.1 Production

Energy generation is provided by production companies that own and operate power production assets, which are mostly hydropower plants. Most production companies are owned by the municipalities and counties, and their operation is based on maximization of social welfare [4]. The trade of power is facilitated by the market coupling operator Nord Pool, which serves as the power exchange for the Baltic and Nordic countries. Production companies place hourly bids and capacities, which Nord Pool uses to determine the market price of electricity for each hour, known as the spot price.

2.1.2 Distribution

The local distribution is handled by distribution system operators (DSO). These companies are heavily regulated monopolies that operate based on area permits granted by the NVE [5]. NVE is acting as the regulatory authority for all DSOs through a department called the Energy Regulatory Authority (RME)[6]. DSO companies are financed by the end-users through a grid tariff that, in 2022, consists of a flat annual rate and a variable cost based on consumption, however changes to this structure are due to be implemented and will be discussed further in Subsection 2.2.2.

2.1.3 Retailing

Due to the complexities of trading power on the power exchange, retailing companies have emerged as an intermediary between the end-user and the power exchange. The retail companies buy power from the exchange, which is resold to the end-user through a sales contract. Power retailing is heavily competitive, and customers are free to choose the preferred company and whether to use the spot price or utilize long-term fixed price plans. Consumes usually pay a monthly flat rate as well as the set price of electricity paired with a markup. Retailing companies are not involved in the physical transfer of electricity, as it is carried out by separate DSOs. The DSOs report the consumption of end-users, which is used as a basis for the electricity bill from the retail company to the end-user [3].

2.1.4 Transmission

The transmission of power is handled by the state-owned enterprise Statnett, which is the transmission system operator (TSO) in Norway. The company has several responsibilities, including operation of high voltage regional lines, handling import and export to interconnected nations, security of supply of the power grid and maintaining the system frequency [7].

Figure 2.1: Norwegian price zones [7]

Since the domestic transmission system capacity is limited, the country has been divided into five price zones, as seen in Figure 2.1. The price within each price zone is determined by the bids of the producers, the expected demand load and the available transmission capacity between the price zones. Due to relatively small capacities on the domestic transmission network compared to the international interconnections, large price differences between the price zones can occur. Price zones NO1, NO2 and NO5 are often balanced at one price, while NO3 and NO4 are balanced at another. This is mainly due to capacity limitations in the NO3-NO1 and NO3-NO5 connections [8], as well as higher demand in the southern zones.

2.1.5 Prosumers

Electricity consumers that also produce electricity up to 100kW are defined as prosumers. Prosumers do not pay grid tariff for energy exported to the grid [9]. Examples of prosumers are end-users with installed PV systems, and these costumers can enter into a PV sales contract with their energy retailer. Electricity produced by the PV system that exceeds own consumption can be injected to the grid. The sales price of exported electricity depends on the contract, but generally, the Nord Pool sport price for the relevant price zone is offered [10].

2.2 Consumer price of electricity

In a liberalized market, the price of electricity is determined by supply and demand. As several factors influence both demand and supply, the overall makeup of the price is complex and makes price forecasting a problematic endeavor. Since Norway is interconnected in the more comprehensive European energy grid, the price of energy in Europe also affects the price in Norway, only contained by the capacities of the international connections.

2.2.1 The Day-ahead market and Real time pricing

The spot price of electricity is determined on the day-ahead market facilitated by Nord Pool, where the market-clearing price for the next day is established daily. The producers and retailers submit bids and bets to Nord Pool following the publishing of available capacities on the grid and international interconnectors. The hourly price in each price zone is optimized to intersect the supply and demand price curves, taking network constraints into account. The market participants are obligated to deliver or consume the agreed amount, and potential imbalances are handled at a separate balancing market managed by the TSO [11].

In Norway, the supply is heavily influenced by the state of the reservoirs of the hydropower plants. Since 90% of energy production originates from hydropower [12], the reservoir water level is a significant factor. The production planning of hydropower plant depends on the current and projected reservoir level. Reservoir levels are in turn dependent on the inflow of water into the reservoir, the outflow due to production, and potential spillage. During periods of lower reservoir levels, production is limited, and water is saved for production during periods of high prices, which in turn increases the prices due to lowered supply and reliance on imports. Full reservoirs lead to high hydropower production in order to avoid spillage and act as a reducing factor in the overall price. One example of this is the effect on the prices during the relatively wet year of 2020. During the second half of 2020, the average reservoir levels were record high, reaching a peak of 95.7% of total capacity in week 47, well above the median of 78.4% [13]. This was reflected in the prices, and the average spot price for southern Norway was only 1.22 EUR/MWh, compared to 42.5 EUR/MWh for the same week one year previous [14].

Another significant factor is the import and export of electricity. Since all price zones are connected to at least one other price zone, domestic or international, the price in one zone is affected by the price in its connected zones. Market functions ensure that power will always flow towards the more expensive zone. However, the limiting factor is the capacity of the transmission lines. In periods of high demand, transmission congestion can cause substantial differences between the zones.

On the demand side, the main consumers of electricity are industry with 45.4% of total consumption, services at 20.7% and households and agriculture at 34.1% [15]. The most important factors of the demand in households is heating, cooking, and other household activities, as well as charging of EV if acquired. This is evident in the price peaks that occur in the morning and evening, reflecting the consumption pattern of the average household. Household demand is relatively inelastic, and thus the demand is not very sensitive to changes in the price. The most significant factor in the demand is the outside temperature, which influences the heating needs of each household.

For households that wish to save on electricity cost by varying demand to take advantage of low prices, a spot price contract is a viable option. Retailers offer spot price contract to end-users based on the day-ahead market with mark-up that includes of sales tax. This kind of pricing scheme is referred to as Real-Time Prices (RTP) in this work. Under RTP, each hour has a different electricity price. The average grid load is calculated over one hour and is charged at the price for the corresponding hour. In addition to the spot price, the RTP contains a value added tax (VAT) of 25%, which is added to the spot price and collected by the retail companies on behalf of the government.

2.2.2 Grid tariff

DSOs charge their customers a tariff for the distribution grid based on consumption. In general, the individual DSOs are free to set the grid tariff. However, they are limited in the total revenue they can collect annually by the regulatory framework of RME [6]. Government fees for electricity use are included in the grid tariff, except for value-added tax collected by the Retailer. Before 2022, two components constituted the grid tariff: one annual fee and one volumetric fee based on consumption. In 2022, the grid tariff is due to undergo structural changes to accommodate more efficient use of the grid, based on a proposal by the RME [16].

The purpose of the proposed changes is to redistribute the cost based on the customers' demand for power to better reflect the actual costs of using the grid. The proposal seeks to contribute to a more efficient utilization and development of the grid, as well as fair distribution of cost. Today, 90% of the cost associated with operation and maintenance of the grid are fixed cost that are not impacted by grid use. Only 10% of the costs are directly related to the transmission of electricity from the producers to the customers [16]. These costs are attributed to heat loss due to resistance in the grid during transmission. This heat loss increases with higher grid loads. As a result, grid operators must purchase more energy than they are able to deliver to the customer in order to meet their contractual obligations. Therefore, the most important cost driver is the momentary power consumption and not the total energy use. The transmission and distribution grids needs to be dimensioned after the maximum power demand, which increases as more demand nodes connect to the grid. The proposal seeks to introduce incentives for customers to redistribute the power consumption such that large investments in increased power flow capacity can be avoided [16].

The new tariff structure consists of two components. The first component is a Time of Use (TOU) charge, which is based on volumetric energy consumption and where the rate changes based on the time of day. The proposed tariff suggests one rate for daytime and nighttime use, where the nighttime rate is lower than daytime.

The second component is the measured peak (MP) tariff scheme. Under the proposed MP scheme, the monthly cost is based on the magnitude of the peak load imposed on the grid during the month. The cost is set at a level that is bounded by a power limit set by the DSO. If the peak load exceeds a specific limit, the user will advance into the next level, which increases the total charge which is billed at the end of the month. The peak load is the highest average grid load recorded over one or more hours. According to the DSO Elvia, their levels are 2, 5, 10, 15, and 20 kWh/h [17]. This type of tariff is currently in use for large industrial electricity customers in Norway and thus a natural basis for a new domestic end-user tariff. In the original proposal, the customer's cost level was to be determined retroactively after the end of the month, based on the peak load during the month. In a revised proposal, the MP was the average of the highest peak loads on different days of the month [18]. This makes the optimization problem more complex and challenging to accurately model with the rolling horizon approach.

The Capacity Subscription (CS) grid tariff was first formulated by Doorman [19] and further developed by Pinel *et al.* [20]. Grid import below this level is charged at one cost, and import that exceeds this cost is charged at a higher cost. In a modeling sense, the advantage of this scheme is that the total cost for each hour can be calculated consecutively rather than at the end of the billing cycle. That makes it more suited for the rolling horizon approach. The SC scheme also has the benefit of not excessively penalizing the end-user for exceeding the load limit in one hour while at the same time incentivizing the end-user to maintain a modest grid load.

2.3 Assets for household flexibility

In order to reduce peak loads, mitigate congestion, and avoid investments in increased transmission capacity, power system flexibility can be a viable solution. The IEA defines this as *"the ability of a power system to reliably and cost-effectively manage the variability and uncertainty of demand and supply across all relevant timescales, from ensuring instantaneous stability of the power system to supporting long-term security of supply"*. [21]

Demand-side flexibility, also known as demand response, is the ability of the end-user to manage electricity consumption through incentive or price-based programs [22]. Price-based programs can stimulate demand response through financial incentives and motivate end-users to manage their consumption patterns. Price signals can be incorporated into the grid tariff, as discussed in Subsection 2.2.2, and spot prices can be offered by the retail companies instead of flat price contracts. RTP, TOU, and CS are price-based programs that aim to facilitate demand response through different load management methods. TOU facilitates a method called *Valley-filling* by incentivizing the use of electricity at night in order to reduce the load difference between peak and valley. Similarly, CS facilitates a method called *Peak-shaving*, which aims to reduce the peak loads of the consumer by charging a higher rate for loads exceeding a specific limit [22]. RTP employs both these methods and allows the consumer to adapt to the market by shifting their load in accordance with the electricity price.

In order to facilitate demand response in the domestic among domestic consumers, every household in Norway is fitted with a smart meter, which allows for hourly measurements of the electricity consumption of the household. The user can respond to the price in the market by varying the demand, and users that are price sensitive can significantly reduce their electricity cost.

According to Hofmann and Lindberg [23], at least 39% of Oslo households responded to price signals by reducing their demand during peak hours. However, most end-users are less price-sensitive, and some are more demand inelastic. Seasonal variety also impacts the price elasticities, and one study shows that demand for the winter months in Oslo is relatively inelastic [24]. In practice, this means that the majority of households are not able to change the time of use of electricity due to an inflexible schedule and heating requirements. This is evident in the average spot price of electricity, which correlates to the time most end-users leave and arrive home from work. As shown in Figure 2.2, these peaks occur on average around 08:00-0900 in the morning and 16:00-18:00 in the evening, while the price is usually lowest at 03:00-04:00 in the morning.

Smart metering technology opens up new possibilities in smart control of power consuming units, such that their operation may be regulated with respect to the electricity price. Such units can be defined as flexible assets and include appliances and systems such as electric water heaters, battery systems, interior space heating, and electric vehicle smart charging control systems. In addition, roof-mounted PV can contribute to the overall energy load by reducing the energy needed from the grid at moments of sufficient solar irradiation. This energy can also be stored in a battery for later use or sold back to the grid. Flexible assets allow households with inflexible demand to shift their grid loads without changing their consumption patterns, as flexible assets can offset the grid load at peak hours.

However, for flexible assets to enable load shifting, an intelligent control system must be implemented to ensure optimal operation. The battery should charge at night when the prices are low and discharge during peak hours. The EV should charge at night when it is connected to the house. This simple operating strategy results in an optimization problem where several variables need to be considered, including the battery efficiency, user load profile, price of electricity, and solar irradiation if PVs are mounted to the roof. In addition, several questions around optimal operation arise, such as whether it is beneficial to charge and discharge every day, or wait or price opportunities.

2.3.1 PV systems

Although PV systems cannot be considered as flexible assets as they depend on intermittent solar irradiation, they do serve a purpose in the overall effort to reduce and shift the load imposed on the grid. PV systems allow the end-user to generate power for self-consumption, reducing the load on the grid and supporting the use of flexible assets. In addition, excess production can be sold to the grid, reducing the overall energy cost. In recent years, PV systems are becoming more popular among homeowners in Norway, and demand is increasing with reduced installation costs.

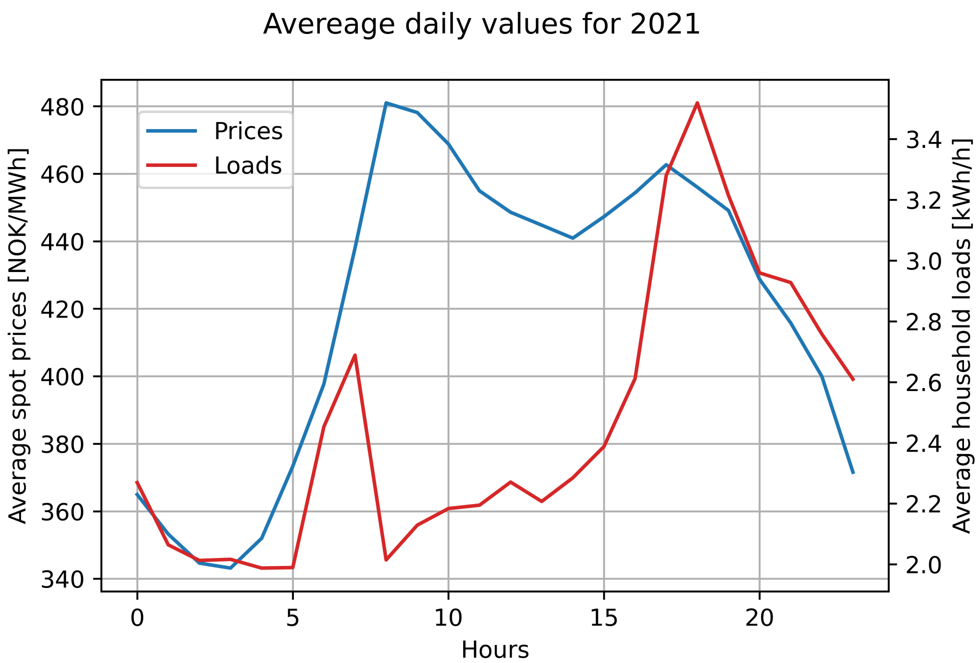

Figure 2.2: Average RTP overlaid on an average end-user load for each hour of 2021, in price zone NO5. Price data gathered from Nord Pool [14], load data from the case study used in this thesis

In the future, PV systems will be more prevalent on new public and residential buildings, and the EU Commission has proposed to obligate installing PV systems on new buildings [25]. Therefore, a high penetration of residential PV is to be expected, and PV systems are naturally included when considering flexibility.

The power output of a PV array is highly dependent on its location and angle. The PV power production data in this project is gathered from simulations provided by the renewables.nija web platform [26], based on the work done by Pfenninger and Staffell [27]. The application has two available source datasets, MERRA-2 and SARAH. In addition to containing more recent datasets, the MERRA-2 was chosen over SARAH as the preferred dataset as it is more consistent on a long-term seasonal basis, even though SARAH is more accurate at individual sites [27]. The MERRA-2 database is a global meteorological reanalysis that contains solar irradiation data based on satellite observations. These data are used as inputs in the simulation model to return estimated PV-power outputs with an hourly resolution for any location. This is done with the use of the Global Solar Energy Estimator to linearly interpolate between grid points to the given coordinates [27].

2.3.2 Battery Energy Storage Systems

One solution to the problem of introducing flexibility into an inflexible end-user schedule is BESS. Batteries can supply some or all of the demand load in periods of peak prices to then recharge during periods of price valleys. When coupled with a PV system, the battery can also recharge using free solar energy instead of drawing from the grid. The biggest challenge to BESS is the efficiency losses when charging and discharging the battery. If the energy is provided by PV, the efficiency loss is not a significant issue, but if the energy is drawn from the grid, the energy lost to heat is already purchased from the grid and is, therefore, an economic loss. In order to ensure cost-optimal operation of the battery, it is essential to ensure that the cost savings from the price delta are more significant than the cost of recharging the battery. If the prices do not vary significantly thought the day, a rigid charge-discharge may not be optimal.

In recent years, the cost of lithium-ion for residential applications has fallen drastically. In 2021, the average cost of a Li-ion battery pack was 132 UDS/kWh, a reduction of 89% from 2010, according to BNEF [28]. In addition, studies have shown that battery packs from retired electric vehicles can receive a second life application as residential energy storage, further increasing the battery service lifetime. Such an application can, in certain conditions, be cost-effective [29] and more environmentally sustainable [30] than a brand-new battery pack.

There are currently several residential BESS packs available on the market. The most known is possibly the Tesla PowerWall with 14 kWh storage capacity [31]. There is also the Nissan xStorage with capacity options of 4.2, 6 and 10 kWh [32], and SonnenBatterie with 5, 10 15 kWh capacity options [33]. Lately, emerging BESS technologies at smaller portable scales, such as the EcoFlow Delta PRO with 3.6 kWh are available [34]. Portable systems can lead to reduced installation cost, greater potential for expandability and easy replaceability, which mean more households may consider adding flexibility to their residence trough BESS.

The authors of [35] developed a two stage dispatch method with the objective of maximizing user benefit using particle swarm optimization. The paper considered a PV-BESS connected to a demand load and the grid, with consideration for time-of-use price strategy and import and export of surplus power to the grid. It was found that the strategy would be economically beneficial for the end user.

in [36] the value of a shared BESS was investigated under an MP tariff and NO3 spot prices from 2020. The study used a receding horizon optimization algorithm. The examined battery had a capacity of 521 kWh and a charge/discharge limit of 200 kWh/h connected to two office buildings, a large PV installation and a heated pedestrian bridge. The study considered 3 different months and examined the cost reduction for each season. The study found that a shared BESS could generate cost reductions 6-7% as well as reduce peak loads by 7-11% when measuring with individual metering.

One challenge to BESS is battery degradation. All chemical battery cells degrade due to the repeated chemical reactions that occur during battery charge cycles. Over time, these changes inhibit the battery's ability to uptake electrons and therefore results in reduction of the effective capacity. The extent of this reduction depend on many factors, such as amount of completed cycles, depth of discharge of each cycle and battery temperature to name a few [37]. The reduction in capacity over time effects the economic utility of the battery, which is difficult to quantify. According to [37], battery degradation is enhanced when the battery is charged all the way to capacity, and discharged close to depletion. Good battery management is therefore important, and the management system should limit the depth of discharge in order to prevent unnecessary degradation. Another challenge to using BESS is the upfront investment cost and payback time. The payback time of a battery varies drastically based on the cost, annual energy consumption, and the energy and grid tariffs used. According to one study [38], the payback time of a 7kWh battery with a 2kW power rating coupled to a 3.8 kWp PV system was 15 years. The study was conducted in the UK, and a TOU grid tariff was considered, as well as a fixed price for energy export to the grid. The study only considered the cash flow in the time period, and did not consider the degradation of the battery that occurs after extensive use. The estimate of 15 yeas is therefore highly optimistic. Payback period, net present value or depreciation calculations will not be performed in this study, as it is considered out of scope.

2.3.3 Electric Vehicles

An EV is a type of car that is propelled by an electric motor and where the energy is typically stored chemically in a lithium-ion battery, as opposed to a car with an internal combustion engine using liquid fuel. As a result of government subsidies, EV sales constituted over half of the total car sales in Norway in 2020 [39]. This is expected to rise in the coming years, following the political guidelines stating that all new vehicles should be EVs or in some way "zero-emission" by 2025. According to the Institute of Transport Economics, the amount of active EVs is expected to rise to 61.2% of the total vehicle fleet by 2040 [40]. As a result, a significant number of households will possess an EV in the future, presenting an opportunity for flexibility in households. According to NVE, over 90% of owners charge their EV at home using charging points that deliver up to 3.6kW, 7.3kW, or 22 kW [41]. This makes the EV one of the units with the highest rated power of all household appliances. Thus, the EV is a significant contributor to total household power consumption.

Like ordinary cars, the EVs main purpose to be a personal transportation vehicle. Despite this, they are on average, parked at home 80% of the time and only on the move 4% of the time [42]. When parked and connected to a charging station, the EV can be considered to be a battery from the grid perspective. Flexibility in EV charging can be achieved by controlling when the charging occurs. With a smart charging system, the time and rate of charge can be controlled based on price signals. Many such systems exist today, and one example is the Easee home charging box which allows for optimized charging of the car during the lowest priced hours of the day trough integrations with power retail companies [43]. According to one study, an optimized charging schedule could potentially yield 67% cost reduction compared to standard charging under RTP [44]. However, cost savings heavily depend on the EV and what type of tariff and pricing scheme is considered. The study found that the cost savings were more significant for EVs with higher capacity batteries.

Expanding on the EV flexibility are the novel technologies of Vehicle-to-Grid (V2G) and Vehicle-to-House (V2H).EVs outfitted with these technologies allow the battery to supply energy back to the grid or the house through bidirectional charging. A possible implementation of V2G is at private or public charging points or home charging stations. V2G technology has been suggested as a solution to the problem of large-scale storage of intermittent energy generation, as opposed to building dedicated storage facilities using li-ion batteries. It has also received interest from grid operators due to its ability to facilitate ancillary services such as load balancing and frequency regulation, thus alleviating some of the burden on the grid [45].

There are several challenges to V2G. One of these is the increased battery cycling in the EV, which leads to accelerated degradation of the battery, reducing the range and the resale value of the vehicle. This depreciation is hard to quantify, mainly because it impacts the vehicle's utility. The cost of degradation might exceed the economic benefit of arbitrage but can be mitigated with the use of intelligent algorithms that optimizes battery cycling and minimizes degradation [45].

On a smaller scale, V2G also applies to the single user through V2H. The rationale of V2H is based on the assumption that, during the two peaks in the morning and early evening, the EV is parked and connected to the home, given that the user follows a regular work schedule. If the EV is sufficiently charged, it could supply part of the power demand during the morning peak by utilizing the battery power and have sufficient energy to complete the daily commute. Upon return in the evening, the battery SOC will be significantly reduced, but the EV will start charging when the price lowers for the night, leaving the battery fully charged for the following day. A lower boundary is needed for the allowed discharge in case an unscheduled trip is required. The feasibility of such a scheme is dependent on several variables, such as the capacity of the battery, the rated power of the charger, the length of the commute, the energy use during the commute, and perhaps most importantly, the range anxiety threshold of the user.

One of the benefits of V2H capabilities is that a high-capacity battery can become available for use for flexibility purposes. It could potentially replace a dedicated battery storage system. An EV can be used for energy storage and transportation, making the upfront investment cost more acceptable as the transport utility of the vehicle is necessary regardless of the V2H capability, making it an added benefit of the vehicle. Another consideration is that the average battery of an electric vehicle is 50-60 kWh and rising, dwarfing most stationary battery storage options [46]. Therefore, V2H capable EVs could become an attractive alternative to a stationary BESS.

There are several disadvantages to V2H. As mentioned, the cost of increased battery degradation might diminish the overall economic return of bidirectional charging. Another disadvantage is the inability of the EV to capture the solar energy production that occurs during when the solar irradiation is the most intense, since the EV is not connected to the building.

EV-V2H optimal charging schedule was explored in [47], where two different stationary batteries and V2H capable EVs were examined in the UK, supplemented by a 3.5kWp PV system. The pricing strategies considered were a flat tariff, a TOU tariff and spot tariff. Similar to this work, a Pyomo optimization model with a Gurobi solver was used to optimize the input data. The authors found that using V2H enabled Nissan Leaf (38kWh) with a TOU tariff could reduce the electricity cost by 85% compared to charging without V2H on a flat tariff. However, in the study, the EV was available most of the time, except for a few short trips of 30min, which does not reflect the habits of the average EV user, who leaves the house for several hours for work. The driving pattern of the user can be unpredictable, which significantly complicates the process of modeling optimized EV charging.

Iversen *et al.* [48] presents a rolling horizon stochastic dynamic programming model for optimal EV charging, with a focus on accounting for the stochastic nature of EV use. The model used a prediction horizon of 48h and a total scheduling horizon of 2.5 months. The EV in question was a Nissan Leaf with a battery capacity of 24 kWh. Spot prices from the DK1 were used to calculate cost, and additional penalty cost was added if the EV was unavailable due to low SOC when the user desired to utilize the EV. No grid tariff was considered. A Markov decision process was used to determine the state of the EV. Daily cost savings ranged from 19-47 % when only utilizing optimal charging. In the study, V2G was also investigated, and it was found that the user could not only reduce cost but also profit from an optimized V2G scheme with a total cost reduction of 135% when the EV was always available. However, since no grid tariff or taxes were considered, this profit is unlikely, and quantifying the value of an unavailable vehicle is very subjective.

2.3.4 Domestic Hot Water

DHW refers to the preparation and use of hot water. In Norway, the hot water used in most households is prepared in electric water heaters (EWH) installed in each home. The energy consumption of each water heater depends on its volume and temperature settings, however, the mean energy consumption is around 3000 kWh [49]. After space heating and EV, the EWH is the appliance with the highest energy use in households [49]. Usually, the water is kept at a constant temperature throughout the day, despite the majority of the hot water demand being concentrated at a few hours of the day, usually morning and early evening.

Modern, well insulated water tanks can hold the temperature of the water at a reasonably comfortable level for several hours after heating. Electric water heaters represents a flexibility potential as the water can be heated before the price peak hours, and thus decrease RTP cost. In addition, the water heater can be turned off during periods of inactivity, such as during the night and the work shift.

Studies into DHW flexibility have mainly revolved around peak shaving. Flexibility potential in the form of demand response was studied in [50], where a Norwegian case study was examined. The authors simulated 1000 households, each with one electric water heater capable of switching on and off based on DSO activation signals. It was found that the highest average power flexibility potential was 53.9% of total capacity at hour 8 of the day. However, the use of DHW flexibility cause a considerable rebound of power use after the flexibility activation, if proper precautions are not taken. Rebound could be reduced by optimally scheduling the DHW activation.

Ericson [51] analyzed data from 475 Norwegian households where the water heaters had been disconnected based on a signal during peak hours. The author found an average load reduction between 0.18 and 0.59 kWh/h per household. Load control of EWHs was found to be an effective tool in reducing peak load consumption. However, the strategy was found to cause a significant rebound in consumption after reconnection, up to 0.28 kWh/h, which increases the risk of a new peak in demand if they were all switched on simultaneously.

These studies focused on demand response based on a signal sent from an external actor. In this work, the control is based on optimal operation of individual units in response to pricing schemes. One study [52] formulated a unit-commitment algorithm for scheduling a EWH based on consumption and day-ahead price forecasts. The study considered a 24h horizon and found that the control scheme could yield 20% cost savings without compromising user comfort. This was achieved by lowering the temperature interval from 61°C - 71°C in the reference case to 54.5°C - 65.5C°C in the time interval 13:00-17:00. This suggests that lowering the required temperature can financially benefit the end-user.

The Norwegian Institute of Public Health recommends that the minimum internal temperature of a EWH is 70°C in order to minimize the risk of legionella contamination. However, variations are acceptable if the water is regularly heated to 70°C. The minimum temperature threshold set by the institute is 55°C [53]. The temperature limits can be set such that the water is heated to a comfortable temperature in the morning and evening and relaxed to a low limit of 55°C during the rest of the day, as done in [52].

2.4 Home Energy Management System

In order to schedule one or more flexible assets, a home energy management system (HEMS) can be used to achieve cost-optimal operation with inputs such as price signals and load forecasts. With flexible assets connected to the HEMS, their use can be governed based on an optimal dispatch strategy that minimizes the total energy cost associated with importing electricity from the grid. However, the input signals are subject to uncertainty. The Nord Pool spot prices are only available 24 hours in advance, and price forecasts decrease in accuracy with increasing time horizons. The loads from the house are subject to uncertainty as well. The heating demands are dependent on the outside temperature, which can be somewhat accurately predicted by weather forecasts a few days in advance. Load demand from the EWH is also challenging to forecast as it depends on stochastic user demand. However, if the user sticks to a lifestyle of habitual use, it can be predictable. This is also true for the EV, which usually follows a set habitual time frame.

In addition to the references in the previous section, there are several works that examine the optimal operation of flexible assets using HEMS. In [54], a HEMS scheduling model is developed for controlling a BESS, heating, and home appliances, using RTP and MP tariff schemes. Several flexible assets are included such as an 1.5kW air-condition, 8 kWh battery, 4kWp PV system, as well as ordinary household appliances such as a coffee machine. The authors use a metaheuristic optimization algorithm to solve a nonlinear objective function. The scheduling horizon considered is 24h and the control horizon is 10 minutes. The model is run over one month horizon.

The study [54] found that the model was able to reduce the total cost of operation in an Australian household by maintaining the grid load below the historical peak and thus avoiding high MP tariff penalties. The BESS operation was able to secure cost reductions under the RTP scheme. However, when disregarding the MP tariff, the model was able to significantly reduce RTP costs but resulting in high peak loads. Over one month, the HEMS was able to reduce the total cost by two-thirds compared to no HEMS or BESS. One of the exciting relationships to study when combining RTP and MP cost is whether the model prioritizes to reduce peak load and thus the MP cost, or fully utilize RTP price differences to decrease RTP costs. A defined constant was used to determine the weight placed on the RTP over MP priority, but both low and high values produced nearly the same result, although a larger weight on RTP yielded a slightly lower total cost. The long-term value of operation was not explored further.

In [55] Thorvaldsen *et al.* examined the long-term value of the operation of a HEMS and how flexible assets impacted the operation. The flexible assets considered were EV, BESS and interior space heating. The horizon considered was the month of January 2017. Each asset was investigated individually using electricity RTP together with an energy-based tariff and an MP grid tariff. A backward stochastic dynamic programming (SDP) algorithm calculated a piecewise-linear expected future cost curve. The study found that all the flexible assets could reduce the expected cost, the best being the EV with a 14.6% cost decrease compared to a reference case where the other assets were passive in operation. The EV considered was 24 kWh with a capacity range of 20-90%, with a departure requirement of at least 60%. The EV was able to reduce the peak power import by 3.54kW, which reduces costs under the MP grid tariff. The BESS considered were a 10 kWh and a 5 kWh, with a 2.5 kW inverter. Both assets were able to reduce costs by around 10%, but only a marginal difference in cost reduction was observed between them. The 10 kWh BESS was able to cut the expected peak import by 2.5 KW, and the 5 kWh BESS by 2.2 kW, clearly bounded by the inverter capacity.

The key findings of [55] were that the potential for reducing cost was more significant under the MP tariff as cost reductions could be obtained from a reduction in peak load, as well as RTP gains from price differences. However, the total cost was more significant for all cases except the EV under an MP tariff compared to an energy based tariff, using only RTP gains. This is due to the passive behavior of the other assets, increasing the peak load and thus the MP costs. The prices used in the paper were deterministic over the whole period, limiting variation in RTP prices.

The study in [55] did not examine the assets in simultaneous operation in order to capture the impact of each asset. This approach does not consider the impact of aggregated loads of the flexible assets under simultaneous operation, which is key to lowering the peak load imposed on the grid. Simultaneous operation would also reveal the ability of the assets to co-operate in reducing the peak load while also respecting the constraints of each asset. This dynamic was addressed in [56], where the operation of a BESS, EV, PV, and interior space heating was simulated with an MP tariff over a one-month period, using a similar approach as the aforementioned study [55]. The study found that the SDP algorithm reduced the cost by 36% compared to a case where no action was taken to minimize the peak load. However, the algorithm only reduced the cost by 0.3% compared to a strategy of daily peak load minimization. The drawback of this SDP algorithm is the final and initial conditions for the decision variables must be equal at the start and end of each day. This forces the assets such as EV to be charged to a specific value that may not be optimal when considering a longer horizon. This also limits the algorithm's ability to shift the load between the days, increasing the total cost. These studies will be used as a foundation for this thesis. In this work, the simultaneous operation of assets will be examined over a longer horizon and price signal, and the model will determine the condition of the assets through the operating period.

3 Optimization

This chapter presents the optimization model built and implemented as part of this thesis, as well as the background methodology regarding optimization and the rolling horizon approach.

The optimization model presented in Section 3.3 is constructed on the foundation presented in the preceding project thesis [2] and is further expanded in this work. Additionally, the content in Section 3.1, 3.2 and 3.4 were originally part of the project thesis. The content has been reviewed and modified following the objectives of this thesis.

3.1 Linear programming

Optimization is a mathematical field that encompasses methods and models to find the best outcome of a calculable situation. It is often used in decision-making processes to analyze techno-economic systems to identify feasible solutions and find the optimal solution [57]. Linear programming is a method of calculating the optimal value of a mathematical model where the objective can be expressed as a linear function which is limited by a set of linear constraints. The objective function can be the maximization of profits or the minimization of costs [57].

A linear programming problem can generally be written as:

$$\begin{aligned} \min \qquad & z = \sum_{j=1}^{n} c_j x_j \\ \text{s.t} \qquad & \sum_{j=1}^{n} a_{ij} x_j \leq b_i, \qquad i = 1, ...m \\ & x_j \geq 0, \qquad j = 1, ...n \end{aligned} \tag{3.1}$$

Where c_j is the coefficient of the objective function for variable x_j, a_{ij} is the constraint for variable x_j for constraint i. b_i is the limiting coefficient for constraint i. In addition, x_j is limited by a non-negativity constraint [57].

The operation of a BESS is an example of a linear programming optimization problem if the objective is economic dispatch concerning cost minimization. In the short term, the operation of a battery is only constrained by its capacity and power output. Economic dispatch seeks to charge the battery when the price is low and discharge during times when the price is high. The objective function would then be the hourly price times the hourly energy input or output. For more extended operation, more constraints pertaining to battery degradation and temperature limits can be applied.

3.2 Rolling Horizon Optimization

To simulate a realistic operation scenario, the model needs to be confined to a set of parameters that govern the decision process. The spot price of electricity is one of these parameters, which is revealed to the public by Nord Pool one day ahead. This means that the decisions for the planning of the battery operation can only be made for one day with respect to price certainty. The next day, a new dataset is introduced, impacting the new optimal operation. Thus, a new iteration of the optimization model must be performed to account for the new dataset parameters. This logic also applies to the expected output of the PV system, as output is based on the weather forecast, which is improved with more accuracy every day. The expected household electricity demand is also subject to the weather forecast, as colder temperatures increase the demand.

Based on changing parameters, the optimal operation of flexible assets becomes a reactive scheduling problem. In their paper [58], Kopanos and Pistikopoulos formulate an optimization framework for the reactive scheduling of production systems. The rolling horizon method consists of different time horizons, the scheduling horizon (SH), prediction horizon (PH), and control horizon (CH). The scheduling horizon covers the overall operational period that is to be examined and is decomposed into discrete time intervals of equal size. The prediction horizon is based on stochastic prediction data for the next few time steps, where the data within the prediction horizon is considered deterministic. The length of the prediction horizon is determined by the extent to which the prediction data can be considered accurate for each consecutive time step. The control horizon has the same initial conditions as the prediction horizon but with fewer time steps.

The CH values are determined using an optimization method that considers the entire prediction horizon. The CH variables are then used as the initial condition for the next time interval, and the procedure is repeated for the length of the SH. An illustration of this process can be seen in Figure 3.1

The rolling horizon approach has, in several research papers, been implemented as a strategy for the optimal operation of microgrids. The overall goals are different; however, the objective is often to minimize the cost of operation. Thus, the strategy can be carried over to battery energy storage operation concerning cost minimization. Silvente *et al.* [59] applied a two stage rolling horizon framework to a microgrid with different prediction horizon lengths, with the objective of minimizing cost. They concluded that longer prediction horizons improve the optimal operation under the assumption of accurate prediction data.

3.2.1 Rolling horizon algorithm

The first step in the algorithm is to define the system's initial state. In this case, the initial state variable is the BESS and EV SOC, as well as DHW temperature. The initial day is also used to determine the length of the SH, which is one month. The CH is set to 24 hours, and the PH will be set to 72 hours. In previ-

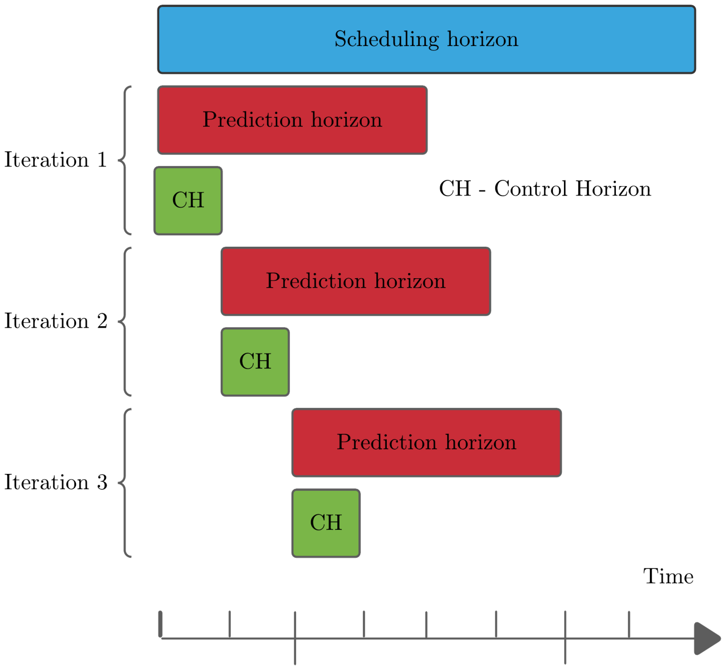

Figure 3.1: Rolling horizon framework. Adapted from [59]

ous work [2] 72 hours was found to be an acceptable PH for this scheduling problem.

For each iteration, optimization is carried out for the set PH. The variables extracted from the CH time step depends on the present assets. The available output variables are the SOC of the BESS and EV, and the temperature of the DHW. These variables are then used as input for the next iteration of the optimization of the new PH. The PH forecast data will also be updated for the new horizon time steps. This process is repeated until the final time step of the SH is computed. Finally, the cost reduction for each CH is calculated and presented as the result for the SH.

A diagram of the algorithm can be seen in Figure 3.2. The diagram represents the iteration process for a given CH, PH, and SH, as well as given initial state parameters. Even though the optimization is performed for the entire PH, only the values pertaining to the CH will be used for the solution of the iteration. For each iteration, the values used in the optimization is updated to account for new information and forecasting.

As the end of the scheduling horizon approaches, the prediction horizon will extend beyond the scheduling horizon. Data from beyond the SH is considered to be unavailable and can not be included in the optimization of the PH. As a result, the PH must be reduced with the same number of time steps as extends beyond the SH. At the final time step, the PH will have a length of one time step.

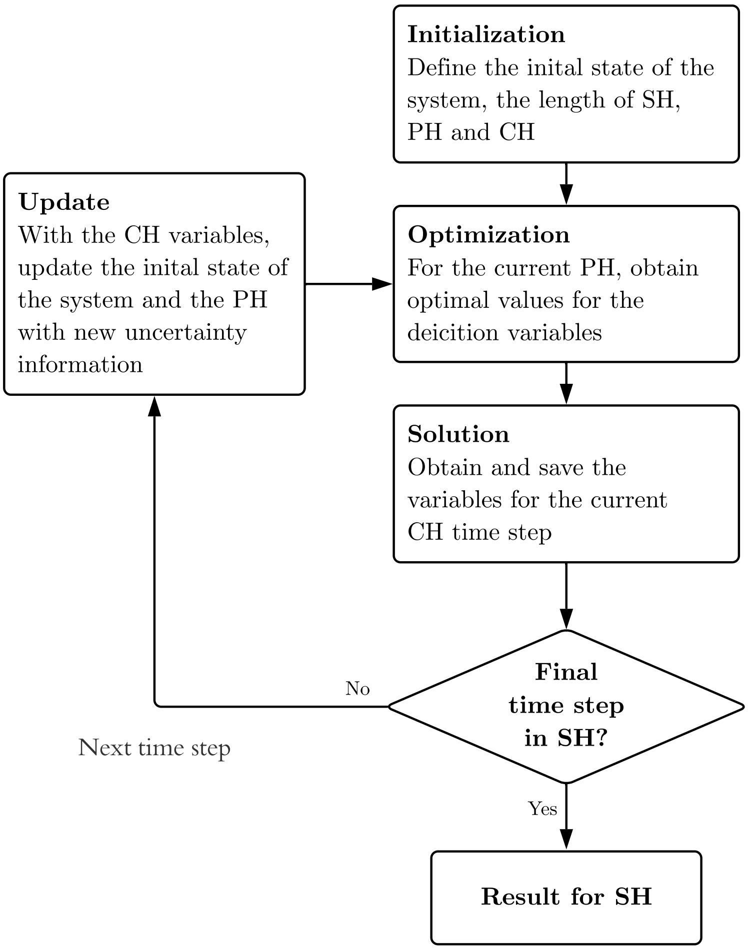

Figure 3.2: Rolling horizon algorithm diagram

3.3 Model Description

This model describes the optimal operation of specific flexible assets in a local household energy system governed by a HEMS. The model accounts for the inflexible household load and load input from a local PV system and governs the charge and discharge profile of the flexible assets examined in this work: BESS, EV, V-V2H, and DHW. The load inputs and outputs in the system are governed by the energy balance constraints formulated in Equation 3.3. Similarly, local energy balances have been set up for the individual assets. The BESS energy balance is formulated in Equation 3.4, the EV in Equation 3.9 and DHW in Equation 3.17. The objective is to minimize the cost of electricity import trough operation of the flexible assets, and the objective function is formulated in Equation 3.2

Sets:

$\mathcal{T}$	Set of time steps t	

Parameters:

$E^{Bat,max}$	Battery maximum storage capacity	[kWh]
$E^{Bat,min}$	Battery minimum storage capacity	[kWh]
$E^{EV,max}$	EV battery maximum storage capacity	[kWh]
$E^{EV,min}$	EV battery minimum storage capacity	[kWh]
$E^{EV,dep}$	Minimum EV SOC at departure	[kWh]
$E^{0,Bat}$	Initial state of charge of the battery	[kWh]
$E^{0,EV}$	Initial state of charge of the EV battery	[kWh]
η^{Bat}	Battery charging efficiency	[-]
η^{EV}	EV charging efficiency	[-]
P_t^{PV}	PV energy production in hour t	[kWh]
T^{min}	Minimum temperature in the water tank	[°C]
T^{max}	Maximum temperature in the water tank	[°C]
$T^{min,dem}$	Minimum temperature in the water tank during the high demand period	[°C]
T_t^{dem}	Temperature decrease due to water demand and heat loss in hour t	[°C]
t^{dem}	hour of high water demand	

C_w	Specific heat capacity of water	[kJ/(kg K)]
m_w	mass of the water	[kg]
P_t^{house}	Inflexible household demand in hour t	[kWh]
p_t^{spot}	Electricity spot price in hour t	[NOK/kWh]
c^{VAT}	Value added tax on electricity purchase	[NOK/kWh]
c_t^{TOU}	Time of Use grid tariff for hour t	[NOK/kWh]
c^{CS}	Base energy level tariff	[NOK/kWh]
c^{Ex}	Excess energy level tariff	[NOK/kWh]
λ	CS base load limit	[kWh/h]
D^{EV}	EV discharge while driving	[kWh]
t^{dep}	EV hour of departure	[-]
δ_t^{EV}	EV connected to the building [0,1] for hour t	[-]
$y^{Bat,max}$	Rated power limit of the BESS	[kW]
$y^{EV,max}$	Rated power limit for the EV	[kW]

Variables:

$y_t^{Bat,ch}$	Battery energy charged in hour t	[kWh]
$y_t^{Bat,dch}$	Battery energy discharged in hour t	[kWh]
$y_t^{EV,ch}$	EV battery energy charged in hour t	[kWh]
$y_t^{EV,dch}$	EV battery energy discharged to the system in hour t	[kWh]
E_t^{Bat}	Battery state of charge in hour t	[kWh]
E_t^{EV}	EV battery state of charge in hour t	[kWh]
T_t^{wt}	Temperature of the water in tank in hour t	[°C]
T_t^{in}	Temperature increase due to load input in hour t	[°C]
P_t^{wt}	Energy supplied to the water tank in hour t	[kWh]
P_t^{grid}	Energy purchased from the grid in hour t	[kWh]
P_t^{exp}	Energy exported to the grid in hour t	[kWh]
P_t^{CS}	Grid load up to λ in hour t	[kWh]
P_t^{Ex}	Grid load above λ in hour t	[kWh]
C_t^{TOU}	Grid cost associated with the TOU tariff in hour t	[NOK]
C_t^{CS}	Grid cost associated with the CS tariff in hour t	[NOK]

3.3.1 Objective function

The objective of the model is to minimize the cost associated with purchasing power from the grid, with the inclusion of grid tariff. Export of power is considered as a cost reduction. The objective function is as follows:

$$\begin{aligned} \min C = \sum_{t}^{T} P_t^{grid} \cdot p_t^{spot} \cdot c^{VAT} + C_t^{TOU} + C_t^{CS} \\ - \sum_{t}^{T} P_t^{exp} \cdot p_t^{spot} \end{aligned} \qquad \forall t \in \mathcal{T} \quad (3.2)$$

3.3.2 System energy balance constraint

The energy balance constraint states that, for all hours, the sum of energy inputs and outputs to the system must be equal. The sum of energy purchased from the grid, energy discharged from the stationary battery, EV battery and the energy from the PV must equal the sum of the energy going into the house demand load and the load resulting from charging of the battery, EV, and the DHW load.

$$\begin{aligned} P_t^{grid} + P_t^{PV} + y_t^{Bat,dch} + y_t^{EV,dch} = \\ P_t^{exp} + P_t^{house} + P_t^{wt} + y_t^{Bat,ch} + y_t^{EV,ch} \end{aligned} \qquad \forall t \in \mathcal{T} \quad (3.3)$$

3.3.3 BESS energy balance

The battery is also subject to an energy balance constraint. The SOC of the battery at hour t must be equal to the SOC of the previous hour in addition to the charged or discharged energy during the hour, taking into account the efficiency η_{Bat}. It may be counterintuitive to have charging and discharging in the same equation. As the efficiency is less than 1, the model does not charge and discharge the battery at the same time. This approach removes the need for binary variables in the constraint. The state of charge $E_t^{SOC,Bat}$ of the battery is carried over from the previous time step and used as an input variable in the optimization. The energy balance of the battery is defined as following:

$$E_t^{Bat} - E_{t-1}^{Bat} = y_t^{Bat,ch} \cdot \eta^{Bat} - \frac{y_t^{Bat,dch}}{\eta^{Bat}} \qquad \forall t \backslash t \neq 0 \quad (3.4)$$

At the start of the model set, there is no data from the previous hour, so the parameter $E^{0,SOC}$ that contains the initial state of charge of the battery is used in place:

$$E_t^{Bat} - E^{0,Bat} = y_t^{Bat,ch} \cdot \eta^{Bat} - \frac{y_t^{Bat,dch}}{\eta^{Bat}} \qquad t = 0 \quad (3.5)$$

The state of charge $E_t^{SOC,bat}$ must always be within bounds of the capacity:

$$E^{Bat,min} \leq E_t^{Bat} \leq E^{Bat,max} \qquad \forall t \in \mathcal{T} \quad (3.6)$$

The battery load input $y_t^{Bat,ch}$and output $y_t^{Bat,dch}$ cannot be negative or exceed the rated power limit. It is assumed that both charge and discharge power rates are the same.

$$0 \leq y_t^{Bat,ch} \leq y^{Bat,max} \qquad \forall t \in \mathcal{T} \quad (3.7)$$

$$0 \leq y_t^{Bat,dch} \leq y^{Bat,max} \qquad \forall t \in \mathcal{T} \quad (3.8)$$

3.3.4 EV energy balance

$$E_t^{SOC,EV} - E_{t-1}^{SOC,EV} = y_t^{EV,ch} \eta^{EV} \delta_t^{EV} - \frac{y_t^{EV,dch}}{\eta^{EV}} \delta_t^{EV} - D^{EV}(1 - \delta_t^{EV}) \qquad \forall t \backslash t \neq 0 \quad (3.9)$$

At the start of the model set, the parameter $E^{0,EV}$ is used, which contains the initial state of charge of the battery.

$$E_t^{SOC,EV} - E^{0,EV} = y_t^{EV,ch} \eta^{EV} \delta_t^{EV} - \frac{y_t^{EV,dch}}{\eta^{EV}} \delta_t^{EV} - D^{EV}(1 - \delta_t^{EV}) \qquad t = 0 \quad (3.10)$$

The state of charge $E_t^{SOC,EV}$ of the EV battery must always be within bounds of the battery capacity:

$$E^{EV,min} \leq E_t^{SOC,EV} \leq E^{EV,max} \qquad \forall t \in \mathcal{T} \quad (3.11)$$

The EV SOC is required to be above a set minimum $E^{EV,dep}$ at a specified time of departure t^{dep}. This is to ensure that there is sufficient charge for the daily commute of the vehicle:

$$E^{EV,dep} \leq E_t^{SOC,EV} \qquad t = t^{dep} \quad (3.12)$$

The charge and discharge of the EV must be within the bounds of the rated power limit. This limit is assumed to be the same for charge and discharge.

$$0 \leq y_t^{EV,dch} \leq y^{EV,max} \qquad \forall t \in \mathcal{T} \quad (3.13)$$

$$0 \leq y_t^{EV,dch} \leq y^{EV,max} \qquad \forall t \in \mathcal{T} \quad (3.14)$$

3.3.5 DHW energy balance

In this model, the electric water heated is treated as a single body with uniform overall temperature. When warm water is used, cold water enters the tank and the average temperature is reduced.

The model must ensure that the temperature of the water in the tank T_t^{wt} at all times stays within the bounds to prevent overpressurization of the tank due to high temperature, and to limit the risk of bacterial growth by maintaining the temperature above a lower threshold:

$$T^{min} \leq T_t^{wt} \leq T^{max} \qquad \forall t \in \mathcal{T} \quad (3.15)$$

The increase in temperature T_t^{in} of the water is determined by the amount of heat added to the water tank each hour. Based on the heat transfer equation, the load input to the water tank can be found using the mass of the water in the tank m_w, the heat capacity of water C_w and the desired increase in temperature T_t^{in}. The resistive heating element in the water tank converts all energy to heat, therefore the load input is assumed to be equal to the heat output in the tank, without any efficiency losses. Thus, the load input can be formulated as:

$$P_t^{wt} = C_w m_w T_t^{in} \qquad \forall t \in \mathcal{T} \quad (3.16)$$

The change in water temperature in hour t from the previous hour must be balanced with the temperature increase resulting from the load input T_t^{in}, as well as the temperature change as result of water use and heat loss T_t^{dem}.

$$T_t^{wt} - T_{t-1}^{wt} = T_t^{in} - T_t^{dem} \qquad \forall t \in \mathcal{T} \quad (3.17)$$

The minimum water temperature depends on the time of day. To ensure user comfort, the water temperature must be at a satisfactory level during a period of water demand when the user is home and awake.

$$T_t^{min,dem} \leq T_t^{wt} \qquad t = t^{dem} \tag{3.18}$$

3.3.6 Grid Tariff

The approach used in this work is similar to the subscription based tariff presented by Pinel *et al.* in [20], where imported electricity is penalized with a higher pricing level than import below the subscribed capacity. The grid tariff in this study costs has been decomposed into two components: the TOU and SC. The TOU tariff is divided into daytime and nighttime tariffs. This hour based tariff is represented by the parameter c_t, ant the cost is represented by C_t^{TOU}.

$$C_t^{TOU} = c_t^{TOU} \cdot P_t^{grid} \qquad \forall t \in \mathcal{T} \tag{3.19}$$

The second part of the grid tariff is the capacity subscription tariff. The cost is based on the level of power drawn from on the grid for the hour. For all hours when the average grid power demand is below the subscribed capacity level λ, the capacity subscription cost c^{CS} apply. For grid loads that exceed λ, the excess price applies c^{Ex} to the excess grid load that is drawn from the grid above the subscribed level. The grid load can be decomposed into the capacity subscription load P_t^{CS} and the excess load P_t^{Ex}:

$$P_t^{grid} = P_t^{CS} + P_t^{Ex} \qquad \forall t \in \mathcal{T} \tag{3.20}$$

The boundaries of the load variables are as follows:

$$\begin{aligned} 0 \leq & P_t^{CS} < \lambda \\ 0 \leq & P_t^{Ex} \end{aligned} \qquad \forall t \in \mathcal{T} \tag{3.21}$$

Capacity subscription charge C_t^{CS} can be described as the sum of the grid load below the subscribed level and eventual excess loads multiplied by their respective tariffs:

$$C_t^{CS} = P_t^{CS} \cdot c^{CS} + P_t^{Ex} \cdot c^{Ex} \qquad \forall t \in \mathcal{T} \tag{3.22}$$

3.4 Computer implementation

The algorithm presented in Subsection 3.2.1 was implemented in the programming language Python 3.8.8 using the optimization package Pyomo. Pyomo is a open-source software package that supports a diverse set of optimization capabilities for formulating, solving, and analyzing optimization models [60]. The actual calculation was performed by a solver program. The solver used in this project is Gurobi with an academic license provided by NTNU [61].

The script for running the algorithm is available in Appendix A. The algorithm is constructed using a series of for-loops, starting with the month. Packages like datetime and calendar were used to work more efficiently with dates and timestamp values, since the input data was structured in a time series format. For each months' iteration, the length of the month was found and used as the SH, which was divided into time steps consisting of integer days. For the CH, the daily time step was further divided into 24 hours, which was handled by the optimization function.

Functions for extracting the relevant input data for each day were added, with a focus on easy scalability such that the function could be used for any given date and asset. Each asset was given a binary state which could be toggled through an input file, and the optimization model could include only the constraints and variables of the active assets. When an asset is not enabled, the variables pertaining to the asset are parameterized as 0, which allows the same equations to be used in all asset configurations. With the relevant input data, the optimization model could run through a separate function to return results. Inputs for the optimization function were the initial day of the PH, initial SOC for EV and BESS, and the initial temperature of the DHW. The returned state variable for the CH, in this case the 24th hour, was used as input for the next day, while the optimization results were stored and used for comparison to the reference cost. For the reference cases, the static asset loads were simply added to the HL. A function for reducing the PH was also implemented, which would check if the PH exceeded the SH before the next iteration. This was done by comparing whether the month integer at the final day of the PH was different from that of the current month in the SH, and perform PH reduction if that was the case.

4 | Case study

In this chapter, the model presented in Section 3.3 will be applied to a set of cases using load data from a Norwegian household. The household is located in the NO5 price zone and has an average annual energy consumption of 21 MWh. The model will simulate the grid consumption when flexible assets are present, as well as their respective reference cases. Each month from January 2021 to December 2021 will be evaluated, and the results will be presented in Chapter 5.

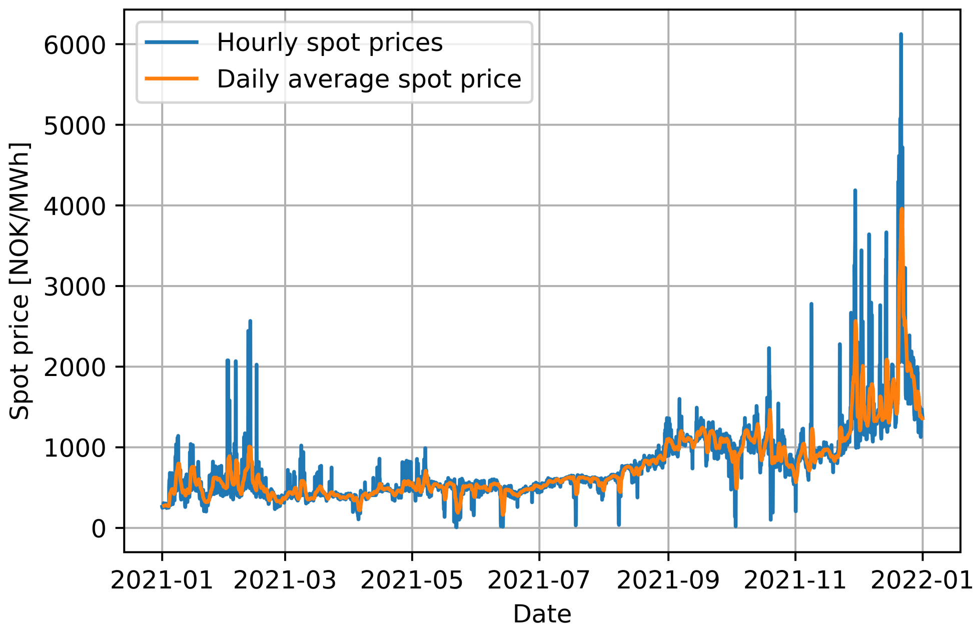

Figure 4.1: Spot price in NO5 over the course of 2021 [14]

The load data of the household was gathered from elhub.no, and belong to a known household in the Bergen area. PV data was gathered from Renewables.ninja [26]. The price data for NO5 was sampled from NordPool.no [14]. The prices in the NO5 price zone can be found in Figure 4.1. For most of the year, the prices are stable at around 300 - 500 NOK/MWh, but large price peaks occur in February and October trough December. In December, the prices are significantly higher than the rest of the year, which is expected to result in high costs.

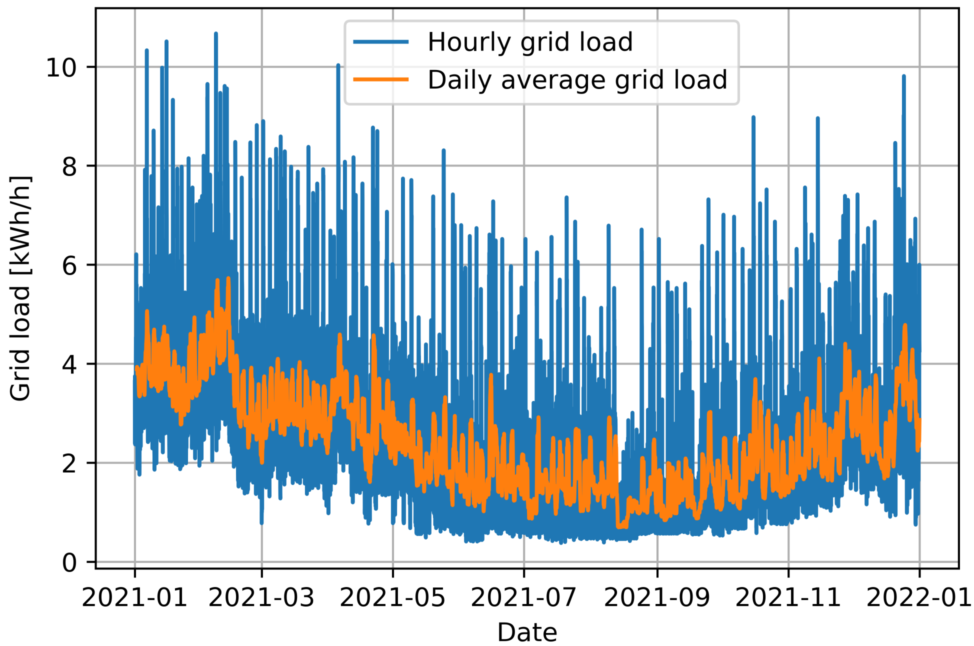

Figure 4.2: Grid load profile for the case household during 2021

The household load (HL) profile can be seen in Figure 4.2. On average, the HL remains between 2 and 4 kWh/h, following the seasonal temperature which governs heat demand. Loads are particularly high in Jaunary due to low temperatures. It should be noted that the HL in this thesis already includes an EV and an EWH. The total load is therefore higher than an ordinary household.

The model was implemented on a personal computer with 2.5GHz Dual-cure i5 processor with 8 GB memory. The runtime was 42 seconds to process one year.

4.1 Case study parameters

4.1.1 PV system

The installed PV system is assumed to have a rated output of 3 kWp. The installation is mounted on a slanted roof of 30°and an azimuth angle of 220°. The latitude of the installation is 60°42' N. These inputs values, in addition to the location of the household, were used in the Renewables.ninja [26] to extract PV production data. In addition, a system loss of 10% was assumed. The suboptimal azimuth angle results in an effective peak output of around 2 kW. The newest available PV data was from 2019, and was adapted for this study. Excess PV power can be exported to the grid at the relevant Nord Pool NO5 spot price.

4.1.2 BESS

The BESS considered is a 5 kWh battery with 95% charge and discharge efficiency and a maximum charge and discharge rate of 2.5 kW, based on the SonnenBatterie [33]. The upper SOC limit is set to 90% of the total capacity, and the lower limit is set to 10% of the capacity. This is to prevent unnecessary degradation of the battery, notwithstanding the lack of modelled degradation in the optimization model. The overview of the BESS parameters is found in Table 4.1.

Table 4.1: BESS parameters

Parameter	EV A	Unit	Comment
$E^{Bat,cap}$	5	kWh	Storage capacity at 100 %
$E^{Bat,min}$	1	kWh	Minimum SOC at all times (90%)
$E^{Bat,max}$	4.5	kWh	Maximum SOC at all times (20%)
$E^{Bat,0}$	2.5	kWh	Initial SOC (50%)
$y^{Bat,max}$	2.5	kW	Maximum power capacity
η^{Bat}	95	%	Charging efficiency

4.1.3 EV and EV-V2H

The EV considered in this study has an 85 kWh capacity battery pack, and is capable of bidirectional charging. The EV is assumed to consume 1.02 kWh/h when disconnected, based on [55]. The parameters apply for both weekdays and weekends. Parameters for the EV can be found in Table 4.2

Table 4.2: EV parameters

Parameter	Value	Unit	Comment
$E^{EV,cap}$	85	kWh	Storage capacity at 100 %
$E^{EV,min}$	17	kWh	Minimum EV SOC at all times (90%)
$E^{EV,max}$	76.5	kWh	Maximum EV SOC at all times (20%)
$E^{EV,dep}$	42.5	kWh	Minimum EV SOC at departure (50%)
$E^{EV,0}$	42.5	kWh	Initial EV SOC (50%)
$y^{EV,max}$	7,2	kW	Maximum power capacity
η^{EV}	85	%	Charge and discharge efficiency
D^{EV}	1,02	kWh/h	Discharge during driving
t^{dep}	8		hour of departure
t^{arr}	17		hour of arrival

The reference case consists of the same EV parameters, but with charging starting at EV arrival charging at maximum capacity until the SOC is at 100%. Since the EV arrival pattern and commute does not change, the charged energy is always the same. The energy used during the commute is 9.18 kWh. To restore the SOC to 100%, 7,2 kWh is charged the first hour and 3.6 kWh is charged the second hour, given 85% charging efficiency.

4.1.4 DHW

The EWH considered is a 200 liter water tank with a 2 kW heating element, based on the OSO Saga S 200 [62]. The heating element is considered to be continuous, and can provide between 0 - 2 kWh of energy each hour. The mass of the water housed in the tank is 194 kg. It is assumed that cold water is refilled into the tank at the same time as hot water is extracted, resulting in constant volume. Internal temperature dynamics of the water tank are not considered, and the temperature in the tank is assumed to be uniform. Temperature decrease is based on a demand profile which includes losses, and temperature increase is based on load input. Since the volume is assumed to be constant, the thermodynamic process of heating the water is isochoric. The specific heat capacity of water is assumed to be constant, and selected at 3.9252 kJ/kgK, which is the isochoric specific heat capacity of liquid water at 70°C [63] .

Table 4.3: DHW Temperature bounds

Time interval	T^{min}	$T^{max,1}$	$T^{max,2}$
06 - 10, 16 - 23	65°C	75°C	90°C
23 - 05, 11 - 15	55°C	75°C	90°C

The demand and load data for the EWH is based on the "Electricity Demand Knowledge - ElDeK" research project by SINTEF Energy Research [64], which examined the average load for each hour using measurements from 49 EWHs in Norwegian households. In order to identify the temperature demand, Equation 3.16 was used to find the temperature increase resulting from the load input in each hour. This is under the assumption that a conventional EWH seeks to maintain the temperature constant at all times, and it is thus assumed that the increase in temperature equals the temperature demand for all hours. The temperature demand in this study is the same for weekdays as weekends. Initial condition for the DHW temperature is 65°C.

4.1.5 Grid tariff parameters

The TOU tariff rate is specified in Table 4.4. The TOU and CS rates are gathered from the DSO Eliva [17], and reflect the prices that were intended for 2022 should the new grid structure be implemented. The rates change based on season, and this is also reflected in the implemented model. The capacity limit λ is set to 5

Table 4.4: TOU rates

Time interval	November - March	April - October
06:00 - 22:00	0.3735 NOK/kWh	0.4170 NOK/kWh
22:00 - 06:00	0.3110 NOK/kWh	0.2920 NOK/kWh

kWh/h. Based on the proposed rates by Elvia, the CS tariff rate is set to 190 NOK for up to 5kW and 280 NOK for up to 10 kW. These rates are charged monthly. Based on this, the CS rates used in this model are the Elvia rates for 5 and 10 kW adapted to hourly rates for CS and excess grid loads. The rates used in this analysis are $c^{CS} = 0.26$ NOK/kWh/h and $c^{ex} = 0.38$ NOK/kWh/h. This grid tariff setup generates a load window of the lowest grid cost between hours 06 and 22, and below 5 kWh/h. This is also the period when spot prices are lowest, thus the flexible asset are expected to mainly utilize this load window.

4.2 Model Cases

This study scope is to examine the long term value of operation for a selection of flexible assets. To that end, each asset operation is evaluated separately, as well as operation of several assets simultaneously. An overview of the cases can be seen in Table 4.5. Cases A-D evaluate one specific asset, while cases E and F evaluate several assets. Case D will evaluate DHW with two different upper temperature bonds, as well as examine the impact of PV on DHW operation. Case E evaluates the load consuming assets, and case F evaluates all assets. Each case includes PV input, and the reference case is run with the same PV input. Excess electricity production is sold to the grid in accordance with the system energy balance.

The goal of the cases is to identify optimal operation patterns of each asset, and to evaluate the long term cost of operation of each asset. In order to determine the

Table 4.5: Model Cases

Case	Asset	Reference
A	BESS	
B	EV	Static EV operation
C	EVV2H	Static EV operation
D	DHW	Static DHW operation
E	DHW, EV	Static DHW and EV operation
F	BESS, EVV2H, DHW	Static DHW and EV operation

long term value of asset flexibility, the cost of operation will be compared to an unflexible reference simulation.

4.3 Prediction horizons

In this study, the prediction horizon is set to 3 days. This is because of the difficulty in creating accurate forecasts several days ahead. The prediction horizon is based on average hourly prices from the past week. For each hour, the average value of that hour is computed based on the previous week. These average values are used for the prediction horizon, while the control horizon is using deterministic data. Therefore, the average values only apply past the 24th hour. Since the forecast is based on past values, the prediction will not be accurate. However, the PH is expected to capture the trends, and therefore serve as an adequate approximation for operational profiles.

5 Results and discussion

In this chapter, the results from the case study will be presented and discussed. Since the electricity bill is comprised of several components, the total cost for each monthly cycle has been decomposed into RTP, CS and TOU cost components, where the sum of these components constitutes the total cost. RTP is the cost incurred by purchasing electricity from the grid at spot price, and includes VAT. CS and TOU comprise the grid tariff. When measuring the cost reduction of each component, the reduction is compared to the same component in the reference simulation.

5.1 Case A: BESS

With a roof mounted PV installation, the user is able to cover some of their demand using the generated electricity. However, most of the solar irradiation occurs during the middle of the day when the demand is generally low. Similarly, when the demand for electricity is high, such as morning and evening, the PV output is lower. Therefore, the PV output can exceed the household demand for the most intensive hours, creating an energy imbalance in the system. Two options present themselves. The energy can be stored in a battery for later use, or sell the excess electricity to the DSO.

In this scenario, the benefit of storing the excess energy generated by the PV installation will be examined. To that end, the model was run with only PV as input in addition to the house demand load. The results are compared to a simulation without any assets other than PV.

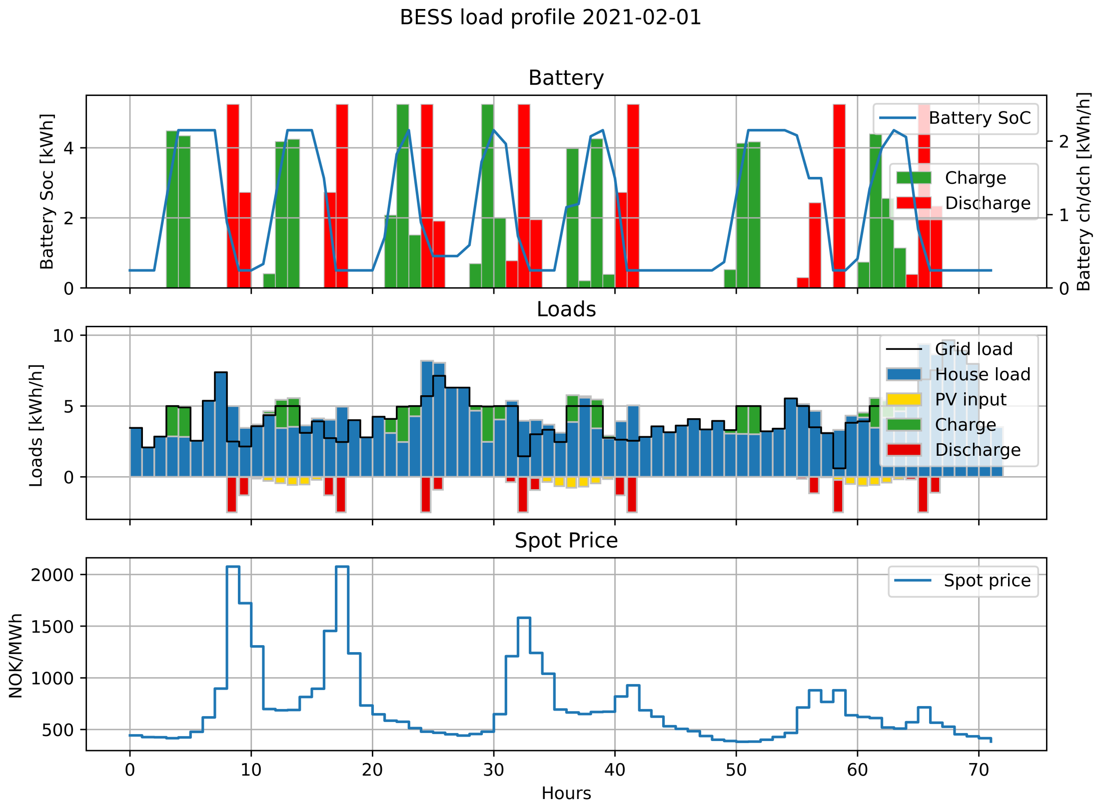

Figure 5.1: One iteration of the BESS load profile, aggregated loads and spot prices for each hour of the prediction horizon

In Figure 5.1 an example of BESS operation can be seen, and consist of one iteration of the optimization model when considering only BESS and PV with a predictive 3-day horizon. The figure consists of three subplots. The first subplot depicts bars that represent the charged (green) and discharged (red) energy from the battery each hour, modelled to the right y-axis. The SOC of the battery is modelled as a line to the left y-axis. In the middle subplot, all the load inputs to the system are modelled. Load that decrease the total grid load (battery discharge and PV) are modelled negative, and load increases are modelled positive. The grid load is modelled as a black line, and represents the total grid load. The final subplot is the spot price of electricity and serves as a comparison for the model behavior, as it is the most important variable price signal.

Recall that only the first 24 hours of the PH are significant, and the following 48 hours is a predictive forecast to determine the optimal state of the decision variables for the next iteration. This particular iteration is characterized by large price peaks, and the BESS is fully utilized to charge in between the peaks, and discharge during the peaks. The battery discharges at full power of 2.5kW during the two price peaks that occur at hour 8 and 17, which reduces the grid load correspondingly.

However, the discharge capacity is too low to cover the entirety of the demand, and the battery is discharged to the lower SOC limit in two hours. This suggests that the battery could be larger and could thus decrease the peak load demand even further. Another observation is that the model tries to maintain the grid load to the CS limit of 5 kWh/h by modulating the BESS charge and discharge rates accordingly. By keeping the grid load below 5 kWh/h, the more expensive CS excess charge can be avoided. Several situations can cause the battery to be unable to maintain the grid load below 5kWh/h. It can be seen that the low SOC limit in hour 25 prevents the battery from supplying enough energy to reduce the grid load to below 5kWh/h.

In other cases, the model prioritizes to utilize the stored energy during the price peaks, as is evident in the discharge during hour 8 and 9, but not 7 when the demand load is higher. On the other hand, The CS limit is usually maintained during charging of the battery.

Figure 5.2 presents the total monthly electricity costs for a reference case with PV input (Yellow column), and PV as well as BESS (Red column). The blue column is the cost without PV or BESS, and serves to illustrate the effect of PV. The highest reduction in cost was seen in July and August with 4.5% cost decrease compared to the simulation with only PV. In the winter, the reductions in cost were 1.5-2%.

Figure 5.3 presents the reduction in each cost component compared to the reference case. As can be seen, both CS, TOU and RTP cost follow the same path without large deviations. Since PV alone does not provide any flexibility, low variations between the different cost components were observed. During the summer months,

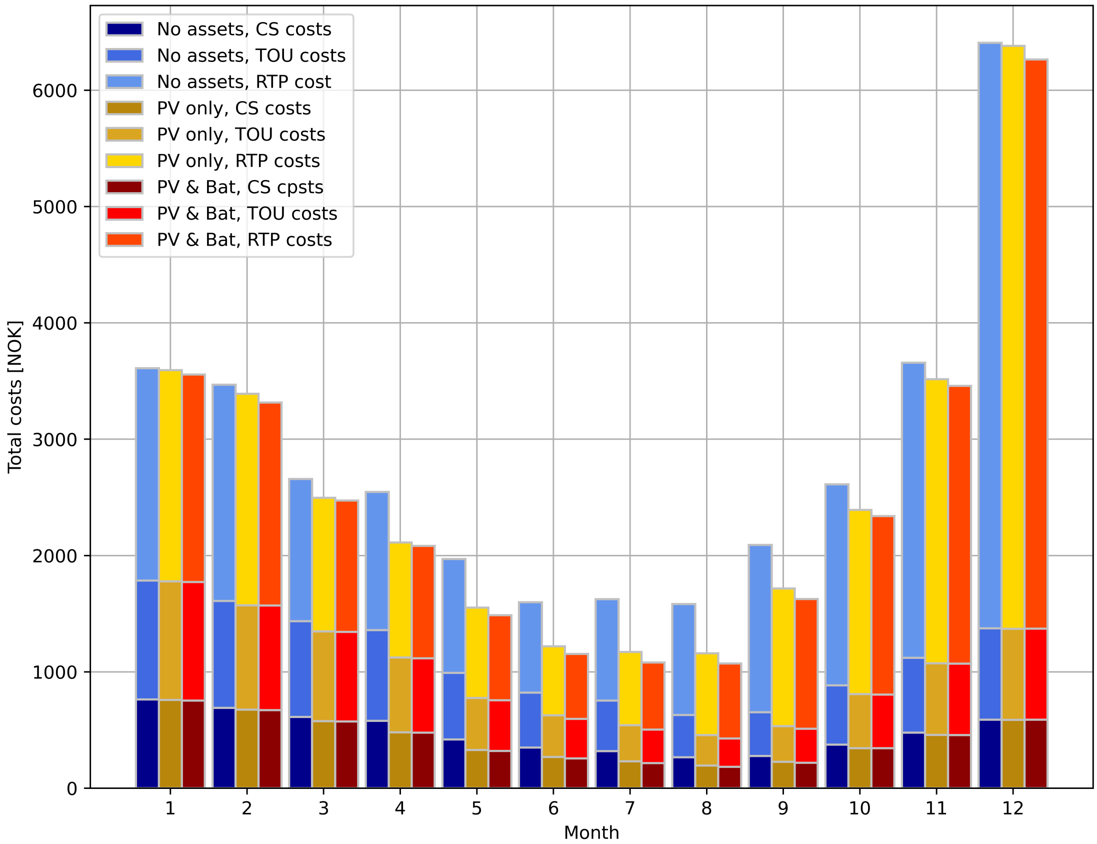

Figure 5.2: Total monthly electricity cost comparison of operation with no assets, PV as the only asset, and with PV-BESS combined operation

the TOU savings are somewhat higher. This is due to the time of day the savings occur. The TOU tariff is more expensive during the day when the solar irradiation is most intense, leading to reduced grid loads during this time. The summer months are characterized by low HL demand, which allows the BESS to better manage the grid load and reduce CS costs. In the summer moths, particularly July, each cost component was reduced with more than 6%, but the total cost reduction was 4.5%. The reason for this is that the excess PV load is sold to the grid in the reference case, thus generating income, while in the BESS case it is used to charge the battery.

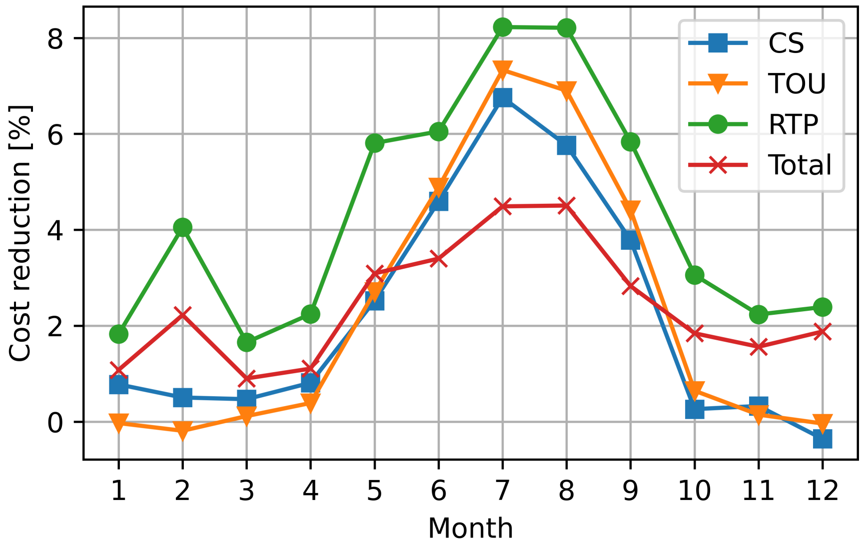

Figure 5.3: Monthly cost reduction of BESS operation compared to the reference case

During the winter months, the TOU and CS costs reductions are not particularly greater with the battery. This is unexpected given the battery's ability to maintain the grid load below the CS limit. Winter months are characterized by high HL demand and low to no PV input, which limits the flexibility potential. However, the RTP cost reductions stand out during the winter months, especially during February, which observed large price peaks. These peaks are avoided by using the BESS power to cover the household demand. Over the course of the year, the total cost reduction was 2%, indicating that the long term value of the BESS does not greatly exceed the value of simply exporting the excess PV to the grid.

5.2 Case B: EV dynamic charging

In this scenario, the benefit of flexible EV charging using the optimization model is examined. For the reference case, a static charging pattern is used for the EV with the same parameters. This charging pattern assumes that the user plugs in the EV after arriving home, and lets the EV charge at full power until maximum SOC is reached. The charging pattern found by the model is compared to a hypothetical daily charging pattern of a price independent user.

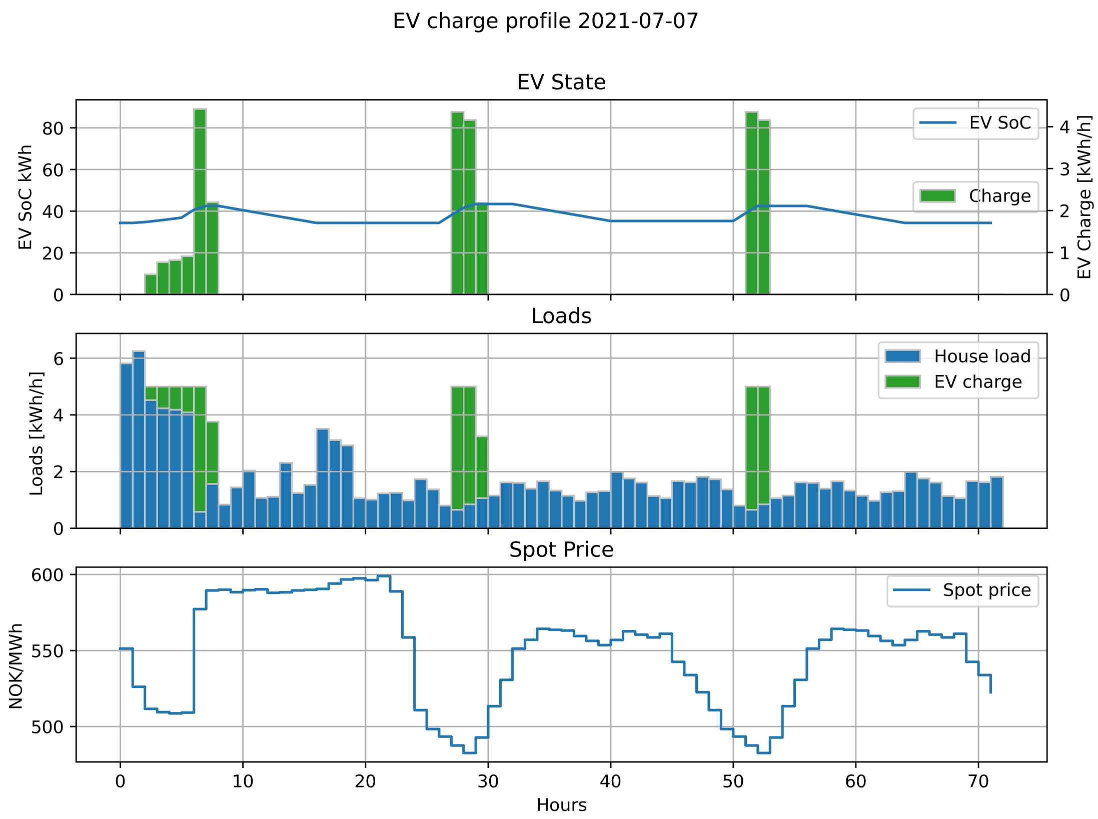

Figure 5.4: EV change profile on a day with clear price peaks and valleys, showing the priorities of the model

An example of the EV charge profile can be seen in Figure 5.4. Like the case with BESS, the model limits the charging profile to only utilize the available power capacity up to the CS limit. Since the inflexible house load is high in this period of the year due to heating demands, the leftover capacity is quite small, but sufficient to charge the battery to the required SOC. The model prioritizes to maintain the total grid load below the CS limit at the cost of charging during higher spot prices, in order to reach the required departure SOC. In addition, the model tends to charge the battery to the minimum SOC requirement at departure once a day. This behavior is not universal. As can be observed in Figure 5.5, the model utilizes the

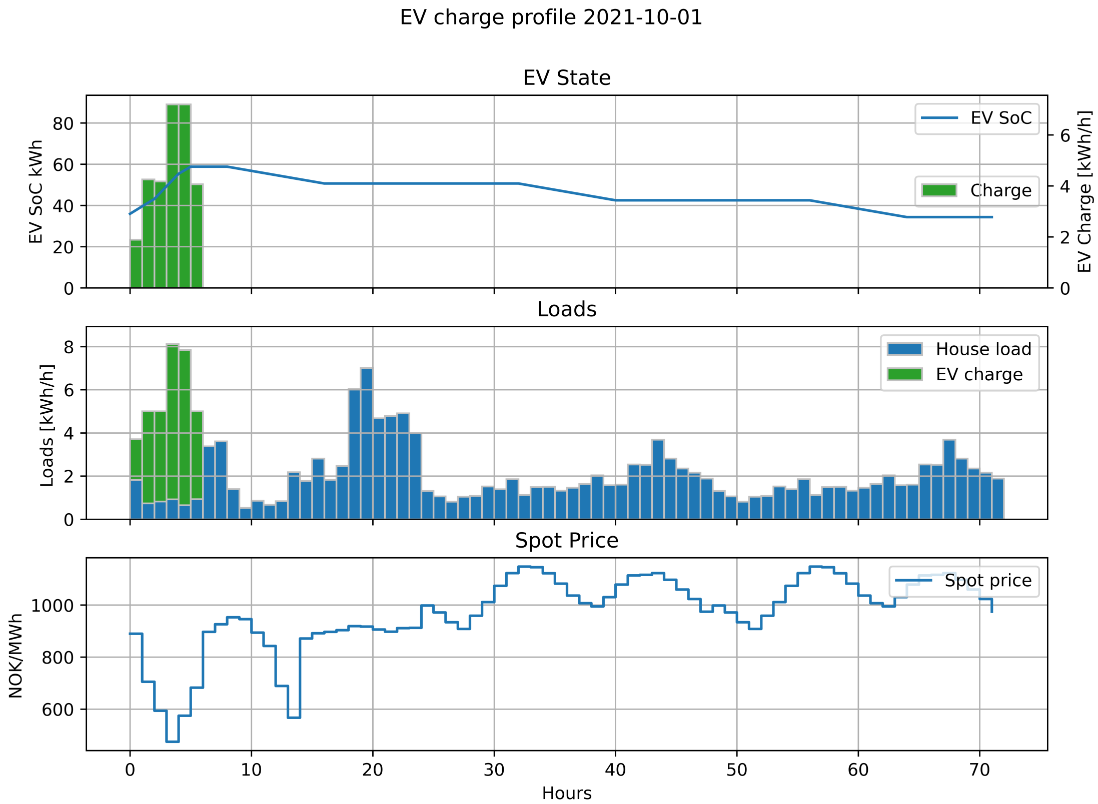

Figure 5.5: EV charge profile in a day with large price differences

price valley at 04:00 and 05:00 to charge at full power and bring the EV SOC well above the required level, even breaching the 5 kWh/h CS limit in order to do so. The reason for this behavior is that the model expects the prices for the coming days to be significantly higher than the current day, so the EV is charged such that it will not need further charging the next two days. However, the optimality of this strategy is uncertain, as the prediction horizon is based on the average of the previous weeks prices. With the price reduction experienced on that day suggest that the future prices may be declining. However, since it is assumed that the HEMS control system does not have access to advanced price forecasts, nor that it can predict the future prices, this strategy adequate in the face of uncertainty.

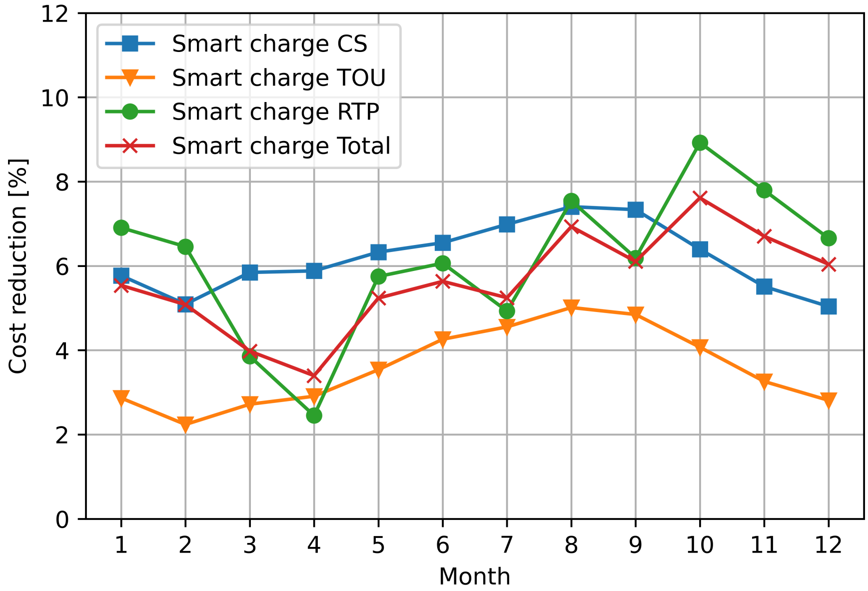

Figure 5.6: Monthly cost reduction of using dynamic EV charging compared to the reference case

In Figure 5.6 the cost reduction of EV smart charging can be seen. In this case, the cost reduction is more sensitive to the variations in RTP, especially the difference between nighttime and daytime prices. The cost reduction peaks in October with 7.9%, which was a month with very high variation in RTP. As a result of smart charging during price valleys, the model was able to secure relatively large reductions. Over a year, the total cost reduction when using dynamic charging was 5.7%. This is interesting given the findings of other authors, such as in [48] where the author found cost reductions of 19-47 %. This illustrates the limiting effect of the grid tariff structure considered in this work.

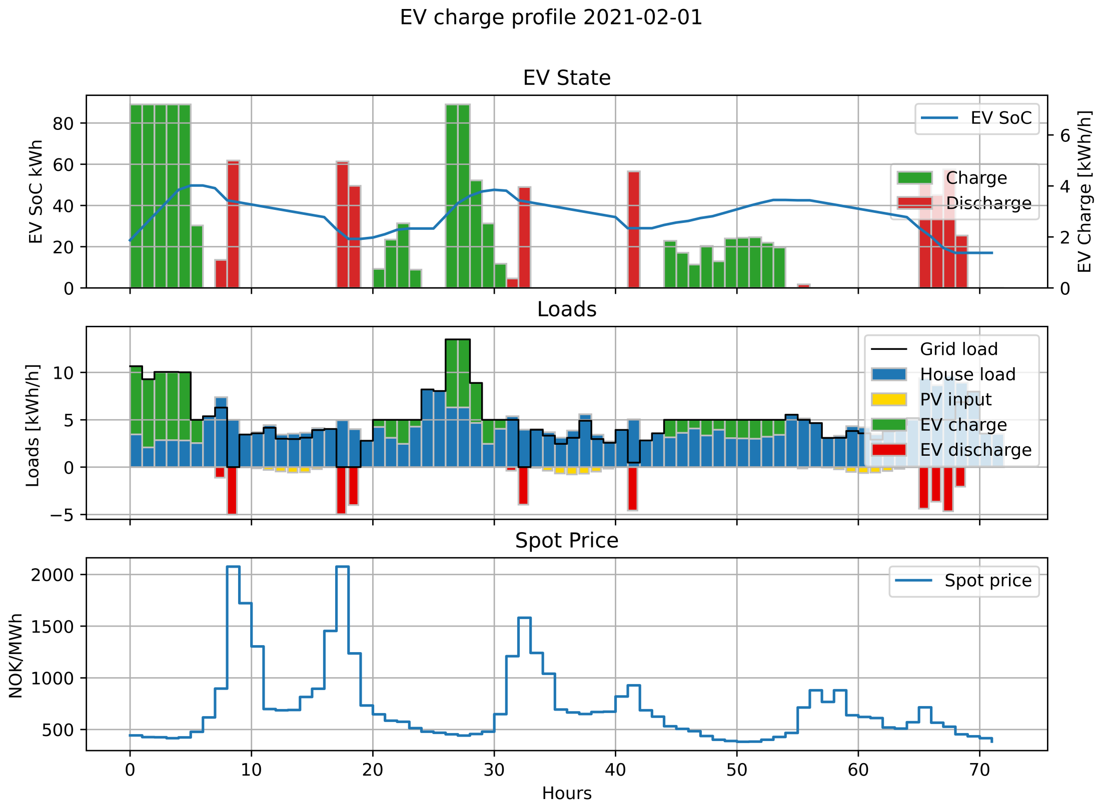

Figure 5.7: EV-V2H charge profile on a day with high price peaks

5.3 Case C: EV-V2H

When adding V2H capabilities to the EV, the ability to discharge power to the system during times of high prices becomes available. As can be seen in Figure 5.7, the battery can be discharged during price peaks like the ones occurring February 1st at 08:00 and 17:00, bringing the total grid load to zero during these hours. In order to accomplish this, the EV must charge at full power for several hours, thus violating the CS limit for these hours. However, the saved cost during the price peaks is worthwhile, as the electricity price for that day is over 300% higher during the price peak compared to the nightly valley in the first 24 hours.

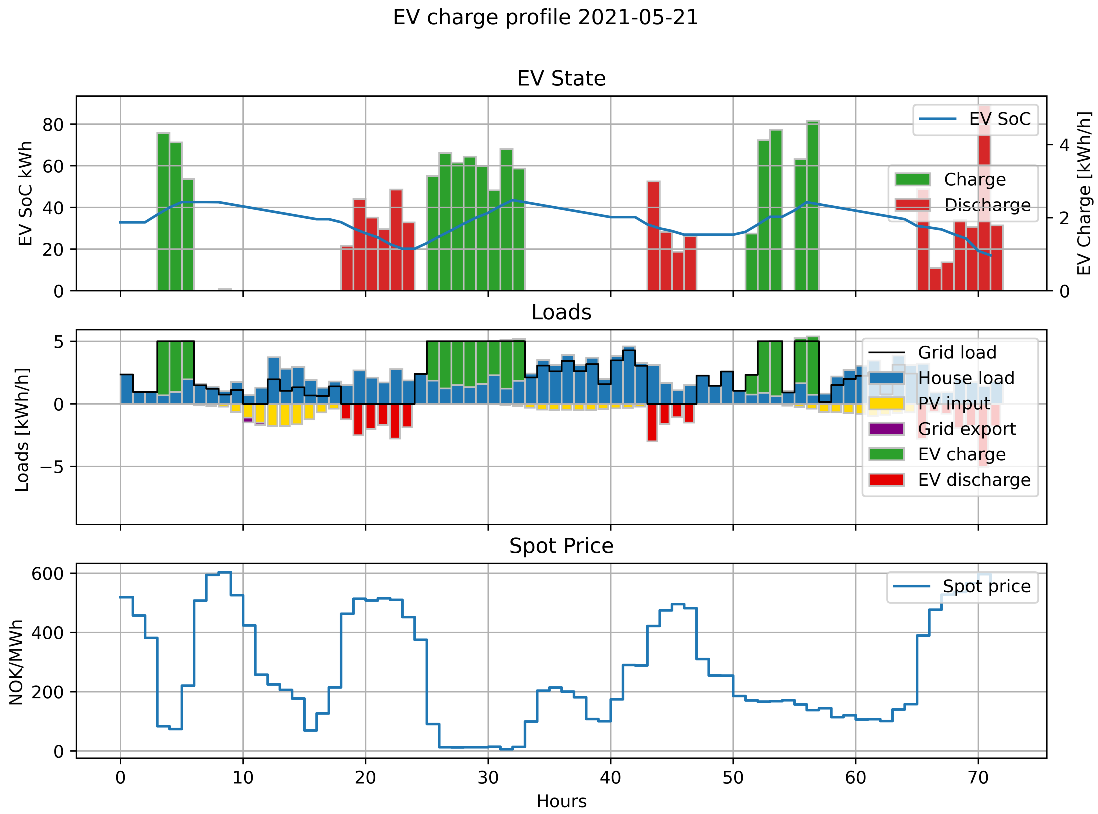

Figure 5.8: EV-V2H charge profile, showing EV discharge during a price peak and subsequent recharge

It is evident that the model seeks to discharge the battery completely at the end of the prediction horizon. This is simply the result of a lack of constraint to be fulfilled at the end. Since the model is finding the optimum across the prediction horizon, the battery is completely discharged to decrease grid load. This has no effect on the overall operation of the scheduling horizon, as it is only the control horizon that has any significance. A 3-day PH will therefore ensure that the behavior has no effect on the long term operation of the asset.

In Figure 5.8, an example of afternoon discharge can be seen. The EV is in this example able to completely supply the house load for six hours until the battery SOC reached close to the lower limit. This was followed by a charging session

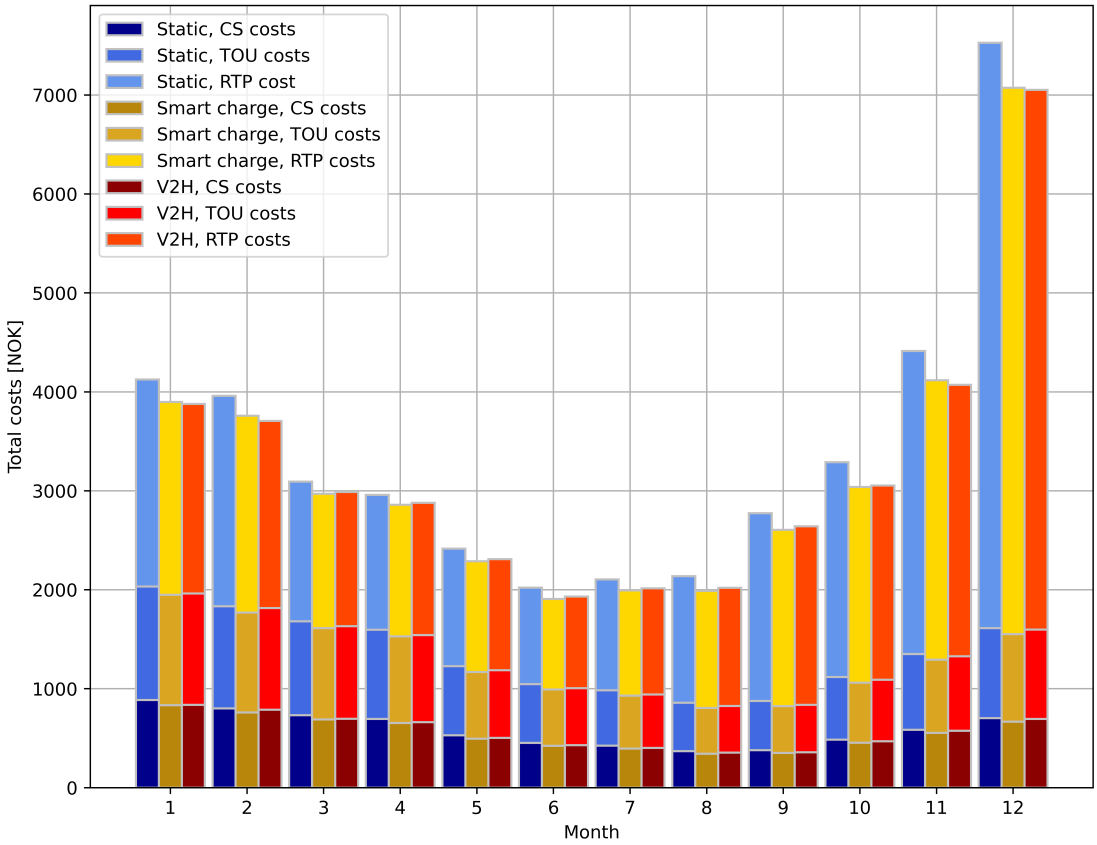

Figure 5.9: Total cost comparison for each month of static EV charging, EV dynamic charging, and EV-V2H charging

lasting 8 hours, and the charge was maintained such that the grid load was bounded to the CS limit. This was achieved despite the SOC being at a relatively low at arrival. Another observation is that the EV is not able to capture the PV energy due to it being disconnected. This energy is used to supply the house load, and excess energy is sold to the grid. PV is therefore not able to support the EV when used as a flexible asset in this setting.

The total cost when using static charging, dynamic charging, and charging with V2H can be seen in Figure 5.9. PV or other assets have not been considered in this comparison. In Figure 5.10 the specific cost reduction in each cost component can be seen compared to the reference case. The model is clearly able to avoid the price peaks by using the available flexibility and thus reduce the RTP cost. However, a tradeoff between RTP and the grid tariff can be observed, as the RTP gains can only be achieved by increasing the grid load between the price peaks, which in turn limits the cost reductions in CS and TOU.

In Figure 5.10, it can be seen that the grid tariff cost component of CS and

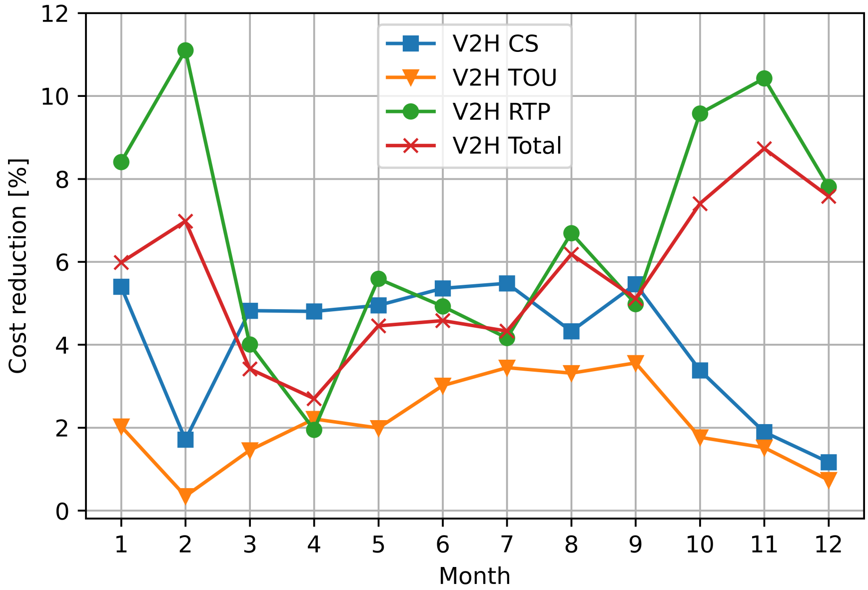

Figure 5.10: Cost reduction using V2H compared to the reference case

TOU decrease in summer and increase in winter. This corresponds with seasonal changes to the TOU price, as well as increase in HL during winter due to heating needs. In summer, the HL decreases, allowing the flexible loads to utilize more load capacity within the CS limit, and to take full advantage of the TOU nighttime tariff discount. From March to September, (with the exception of May and August) the CS provides the largest contribution to the total cost reduction, providing around 6-7% reduction compared to the reference CS cost. The RTP cost reduction vary between 8.9% and 2.4%. Across the year, the total cost reduction was 6.1%, indicating a slight decrease in costs from the EV dynamic charging scenario. The total costs reductions follow a pattern of increasing in the moths of substantial price variations. Based on the CS and RTP cost reductions, the model is clearly able to take advantage of the price differences to charge at cheap hours, and discharge during periods of high HL demand to bring down the grid load. However, in order to meet the minimum EV requirements, charging has to occur regardless of the prices if the SOC is too low, limiting the RTP gains somewhat.

It is clear from Figure 5.9 that using dynamic charging is somewhat beneficial, however V2H does not offer any significant cost savings over dynamic charging in this simulation. This was not expected, given the added flexibility of using the large EV as a dischargeable battery. In Figure 5.10 it can be seen that the RTP cost reductions are significantly higher in winter than in summer, and in turn the CS and TOU cost reductions are lower. The reason for this is that the EV discharges to maintain the grid load under the CS limit and reducing the excess CS cost, but in doing so it consumes more energy from the grid, increasing the base CS costs. The total grid load for each month was consistently higher with V2H, resulting from the efficiency losses of the charge/discharge cycle. With the current efficiency, the economic gains from V2H discharge does not exceed the gains from dynamic charging only, unless the prices have significant differences between peak and valley. As shown in Figure 4.1, such price differences are observed in January and February, as well as September-December, while the rest of the year witness relatively stable prices. This also corresponds to the period when V2H is more profitable than smart charging, as the RTP gains exceed efficiency losses. During stable prices, it may be more prudent to limit grid import and avoid discharging energy from the EV.

5.4 Case D: DHW

DHW was examined with and without PV input, and compared to inflexible operation. The main difference between conventional and smart operation of an EWH is the temperature variation and the distribution of the load needed to maintain the temperature. Large changes in temperature requires large load inputs to raise the temperature fast, while simply maintaining the temperature at a set level requires smaller loads over more hours. Smart operation allows the temperature to drop across the hours of high prices, and utilizing the cheap hours to heat the water. It does not change the total energy used by the EWH, only the time it is used.

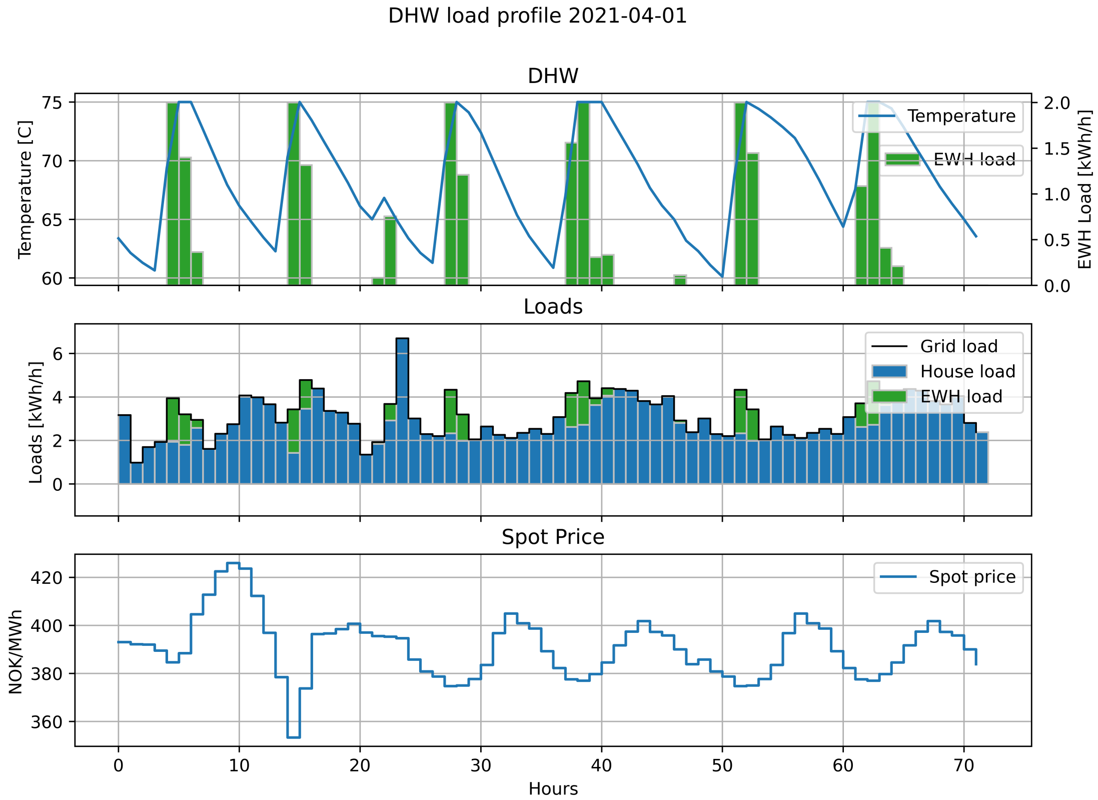

Figure 5.11: DHW operation with 55/65°C-75°C temperature bonds

As can be seen in Figure 5.11, the EHW behaves as intended and maintains the temperature within the required intervals at the right times. In the morning, the EWH heats the water up to the required temperature using the low price interval, and maintains the temperature above 65°C throughout the morning demand period (06-10) and turns off during midday. In the afternoon, it re-heats the water up to 75°C for the evening demand period (16-23). During the evening period, some additional load is required in order to maintain the temperature above 65°C. The water temperature is not given time to drop to the minimum limit of 55°C, and two full heating cycles are needed for each day

One disadvantage to using fixed constraints for the water temperature is that operation ensures that requirements are met, even if that entails drawing power at times of suboptimal prices. This suggests that it may be more optimal to raise the upper temperature threshold in order for the model to have the option to raise the water temperature even further during the cheapest hours of the day. The case EWH can have its temperature adjusted up to 90°C, so setting this as an upper limit is feasible [62].

When the upper temperature is set to 90°C, the model will bring the water temperature all the way to 90°C, operating at full power during the 3 cheapest hours. This eliminates much of the need for re-heating the water during the evening, as the water remains within the comfortable temperature range. At times when the

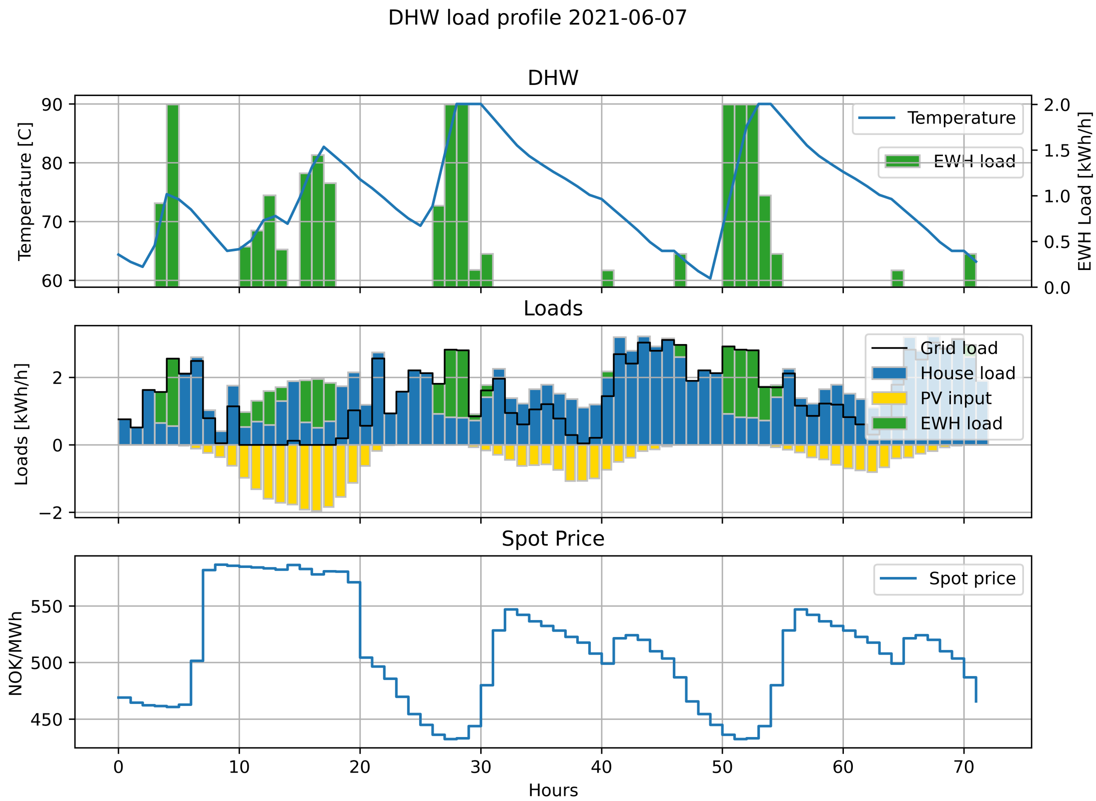

Figure 5.12: DHW operation with 55/65°C to 90°C temperature bounds

PV input is greater than the house load, the excess PV load input is used to heat the water, thus less load is needed in the morning to heat the water. As can be seen in Figure 5.12, the model prioritizes using the excess PV load rather than selling to the grid despite relatively high prices, suggesting that reducing the grid load is more cost optimal than exporting. With a higher temperature bound, the load profile suggest that one heating cycle in the early morning is enough to maintain the temperature above 60°C for the whole day, with only slight heating inputs in the evening. This depends on the initial temperature and the expected PV input. As can be seen in Figure 5.12 the water temperature is only partially increased in the first hours, in anticipation of PV input that could be used to provide free heat

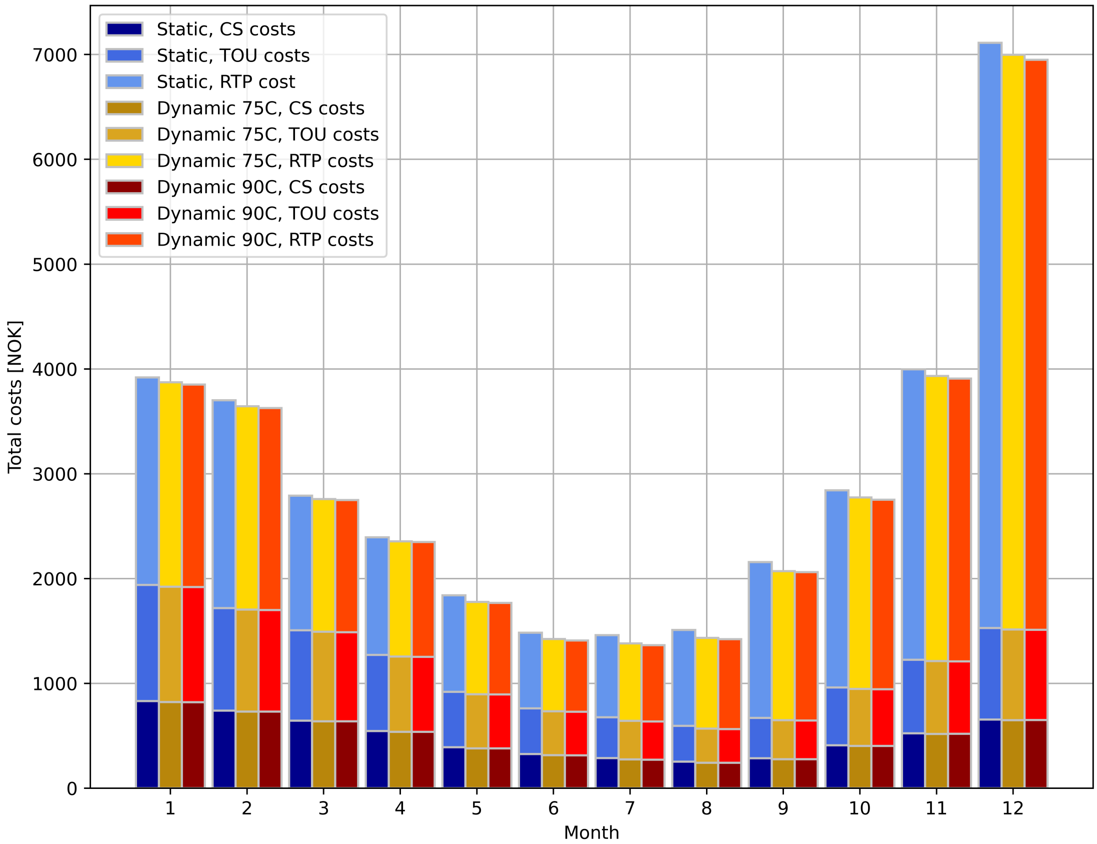

Figure 5.13: Comparison of monthly total cost of static operation of a EWH, as well as dynamic operation with a 75°C and 90°C upper temperature bound

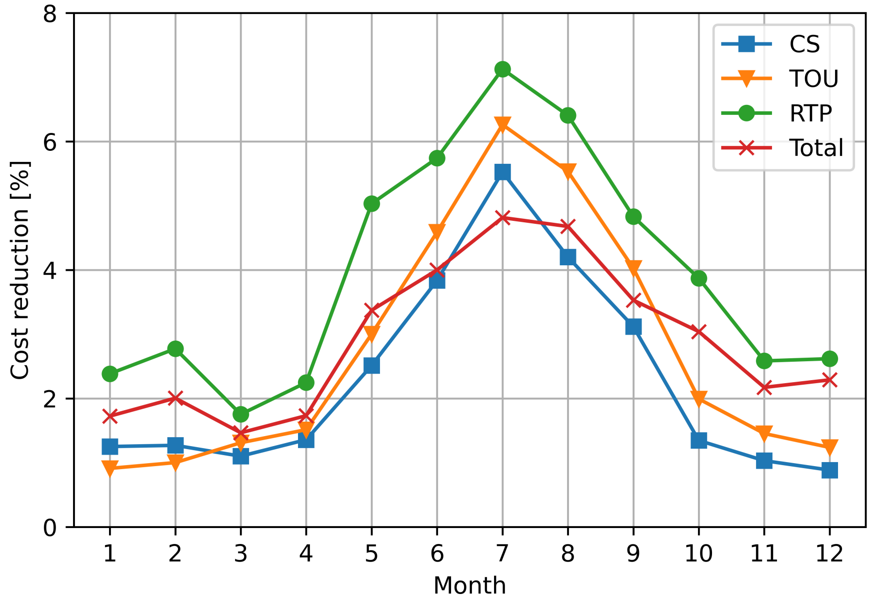

Figure 5.14: Monthly cost reductions of dynamic operation of a EWH with 90°C upper temperature bound and supplemented by PV, compared to static operation

for the coming evening.

Figure 5.13 shows the total cost of dynamic DHW operation with PV input compared to static operation with the same input. Both upper bounds of 75°C and were simulated, and the result is a total cost reduction between 1.16% and 3.97% with a 75°C upper bound, and between 1.4% to 4.8% with the 90°C. It is clear that an upper bound of 90°C offers slightly more opportunity for flexibility, but the overall differences in cost reductions are trivial.

Figure 5.14 shows the total cost reduction compared to the reference case. As can be seen, the cost reduction follows a seasonal trend, with peak cost reduction of 4.8% in July. In winter, the cost reduction remain around 2%. In summer, it doubles to 4%, clearly illustrating the benefit of using the PV input as energy source for the hot water. With PV input, the total yearly reduction was 2.55% with 90°C upper bound, and 2% with 70°C upper bound. Without PV the cost reduction was

2% with 90°C bound.

These simulations disregard the temperature difference between the ambient air and the water temperature. Higher differences between ambient and water temperature leads to greater losses, which in turn leads to more energy needed to maintain the temperature. This aspect has not been examined in this study, which is conducted with assumptions of linear thermodynamic relationships. As such, the pressure changes within the EWH and the resulting strain on the EWH is also not modeled in this simulation. It is not known what the impact of this kind of operation is on the longevity of the EWH. If the result is that the EWH is damaged or in need of early replacement, all economic gains of smart operation could quickly be eliminated. Another aspect that should be noted, is that the temperature demand in this simulation does not correspond to the needs of this particular household, but is rater extrapolated from an average. In this case, the data could be formatted in such a way that the temperature demand would only consist of the estimated heat loss without any water use during the hours that the EV is not connected to the building. However, this was not simulated since the data represents an average over the course of a day.

The energy consumption of the simulated EWH is based on simplified equations and parameters, and is therefore only an approximation of the actual energy consumption. The total yearly energy consumption of the DHW reference data is 2947 kWh. For both the 90°C and 75°C boundaries, the total energy consumption of the simulated DHW was 2802 kWh. This shows that the energy consumption of the DHW model is close to the reference data, with a difference of 5%. The convention factor between load and temperature demand could therefore be slightly higher in order to better match the reference energy use.

5.5 Case E: EV and DHW

This simulation represents the combined flexibility potential of the assets that consume electricity without discharging to the system. The simulated assets are EV and DHW with PV input, and the reference case is static EV and DHW operation with PV. As can be seen in Figure 5.15, the model mainly utilize the night hours to charge the EV and heat up the DHW. This causes the available load capacity under the CS limit to be partitioned between the assets. This results in the EV charging at a lower power rate. Nevertheless, the model is able to fulfill both EV and DHW requirements, using only the optimal load window.

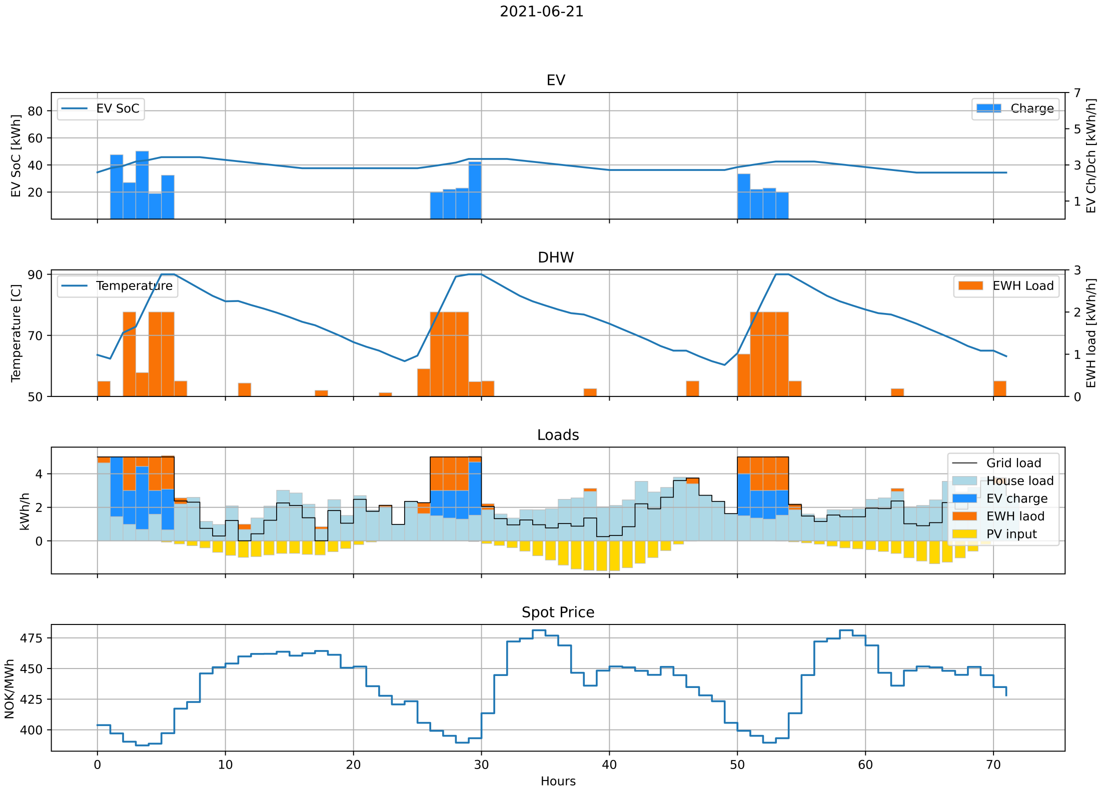

Figure 5.15: Operation of a 85 kWh EV and EWH with 90°C upper temperature bound and supplemented by PV

As can be seen in Figure 5.16, the cost reduction against the base case is around 4%-10% over the course of the year. The total cost reduction over the whole year was 7.08% compared to static operation.

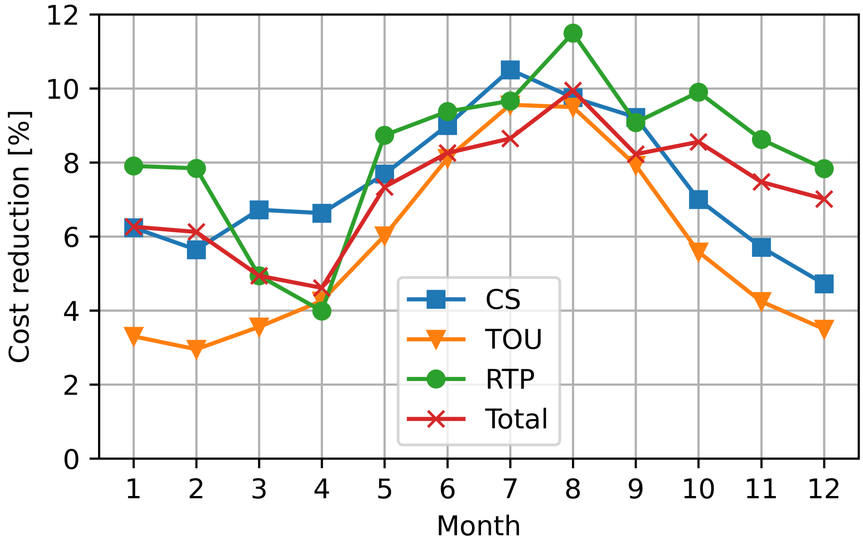

Figure 5.16: Monthly cost reductions of dynamic operation of a 85 kWh EV and EWH with 90°C upper temperature bound and supplemented by PV, compared to static operation

5.6 Case F: BESS, EV-V2H and DHW

In this simulation, all assets are considered, including EV-V2H. The reference case is the HL with PV, as well as static operation of EV and DHW. During simultaneous operation of all the assets, several similar model behaviors are observed. In Figure 5.17, the operation of all assets can be seen. The model seeks to maintain the grid load under the CS limit, and reduce the grid load during peak hours, as observed in previous results. This impacts the loads of each asset, as the optimal load window is congested. The assets with state requirements take precedence over assets without state requirements. Most of the excess PV input is used by the EWH in order to meet the evening temperature requirement, while the remaining PV load is utilized by the battery. The EV also takes precedence over the BESS in order to meet the minimum SOC at departure. This leads to a pattern of limited use of BESS and EV-V2H discharge.

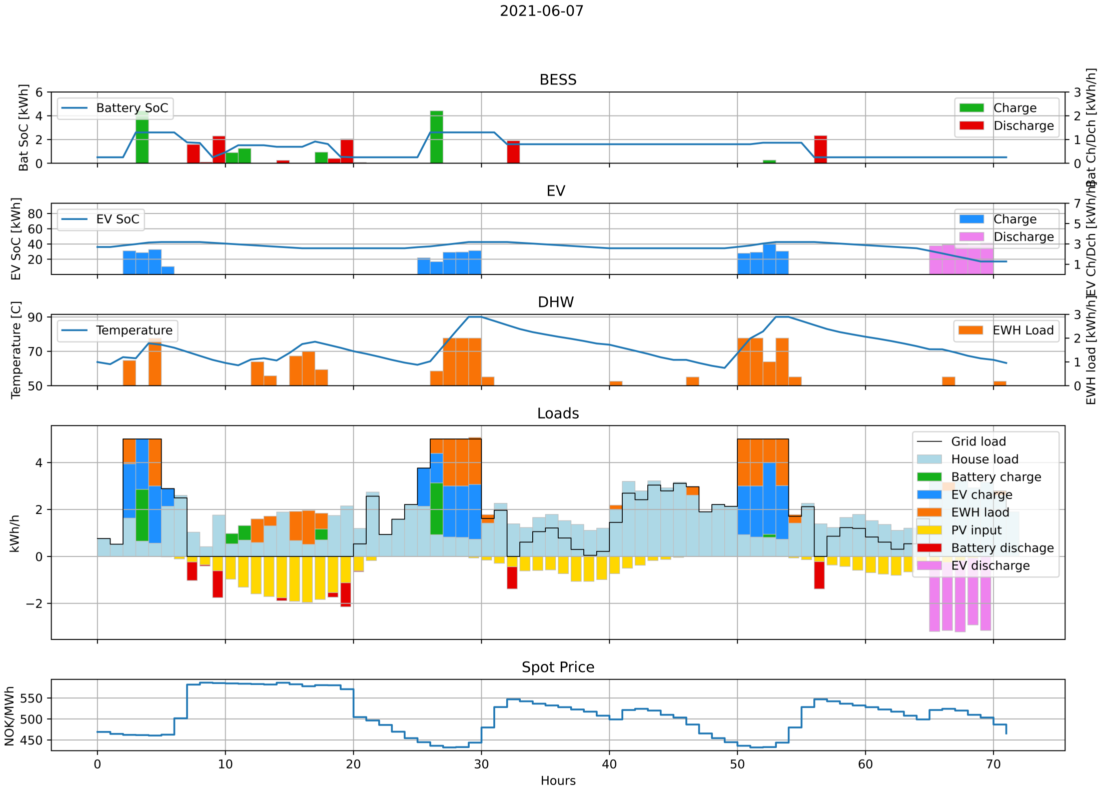

Figure 5.17: Operation of all assets during high PV input

In certain situations, especially in winter, the price variations are extreme, which allows the assets to be fully utilized for demand response. As can be seen in Figure 5.18 the spot price tripled from 2073 NOK/MWH at hour 2 to 6124 NOK/MWH at hour 17, causing the model to prepare the assets in anticipation of this peak. The BESS was charged to capacity and the EV was charged at full power throughout the night. The resulting flexibility allowed the grid load to be reduced to zero during four hours of the evening peak, as well as export to the grid during the two peak hours. The battery initially provides reduction to the grid load until the EV is available to cover the remaining HL demand. In addition, the use of the EV-V2H during the peak depleted the SOC, which causes a rebound in load during the next night for the EV to recuperate the SOC. This strategy may have saved RTP cost, but the resulting grid loads during the night lead to higher CS costs. The peak grid load exceeds 15 kWh/h which would have resulted

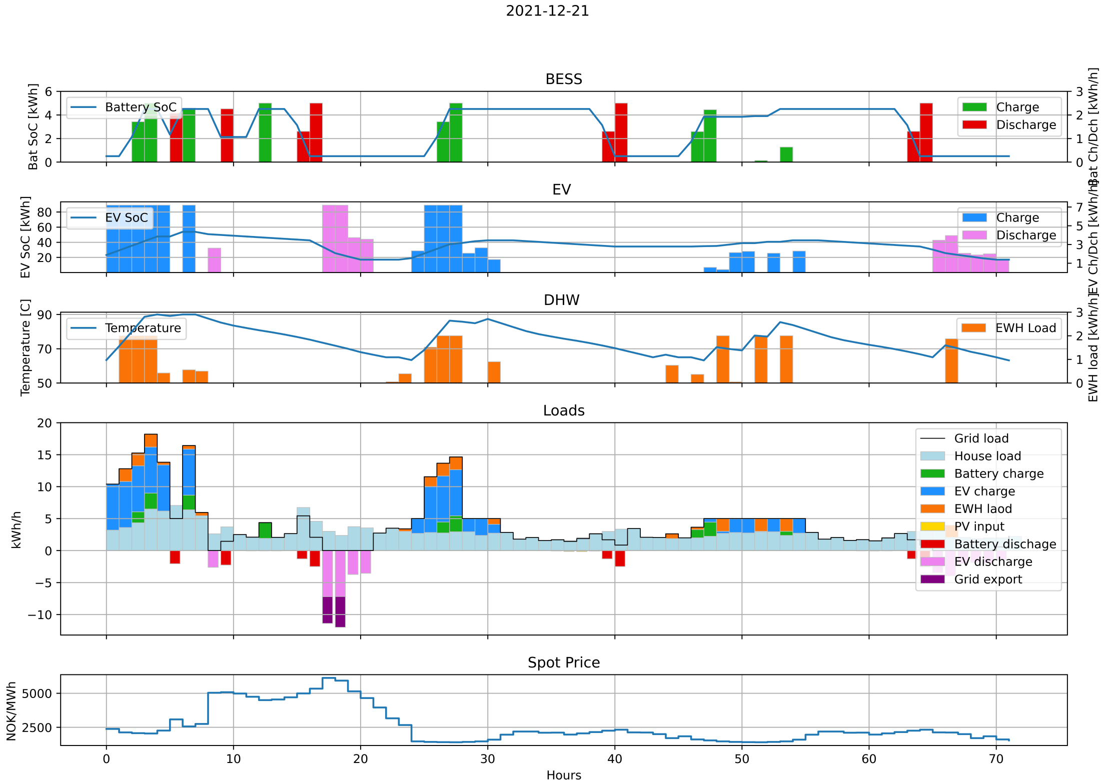

Figure 5.18: Operation of all assets during high spot prices

in a high penalty cost from the DSO if this strategy had been implemented in reality with the suggested MP grid tariff. It should also be noted that the extreme price variation in December were unprecedented and highly irregular. If such events should become more frequent in the future, due to both scarcity of energy resources and permeation of intermittent renewables, it becomes clear that flexible assets can become an important tool in protecting the end-user against extreme price peaks, if an RTP contract is in effect.

In order to determine cost reduction with all assets in dynamic operation, it was compared to the costs of static operation. The total costs can be seen in Figure 5.19. The cost reductions follow a similar pattern as the earlier cases, with greater reductions in the summer due to PV production, with a top reduction of 9.4% in August. During the winter months, some interesting trends can be seen. In

Figure 5.20, it can be seen that the RTP cost reductions were significant even during winter, reaching 9.3% at the lowest in December, and 14.2% in February. In December, the CS cost were greater than in the reference case, due to the high amount of load subjected to the grid above the CS limit. Even so, the total cost reduction amounted to 9% in December compared to the reference case, much due to the avoidance of the price peaks. Overall, the yearly total cost reduction compared to the reference case is 7.93%.

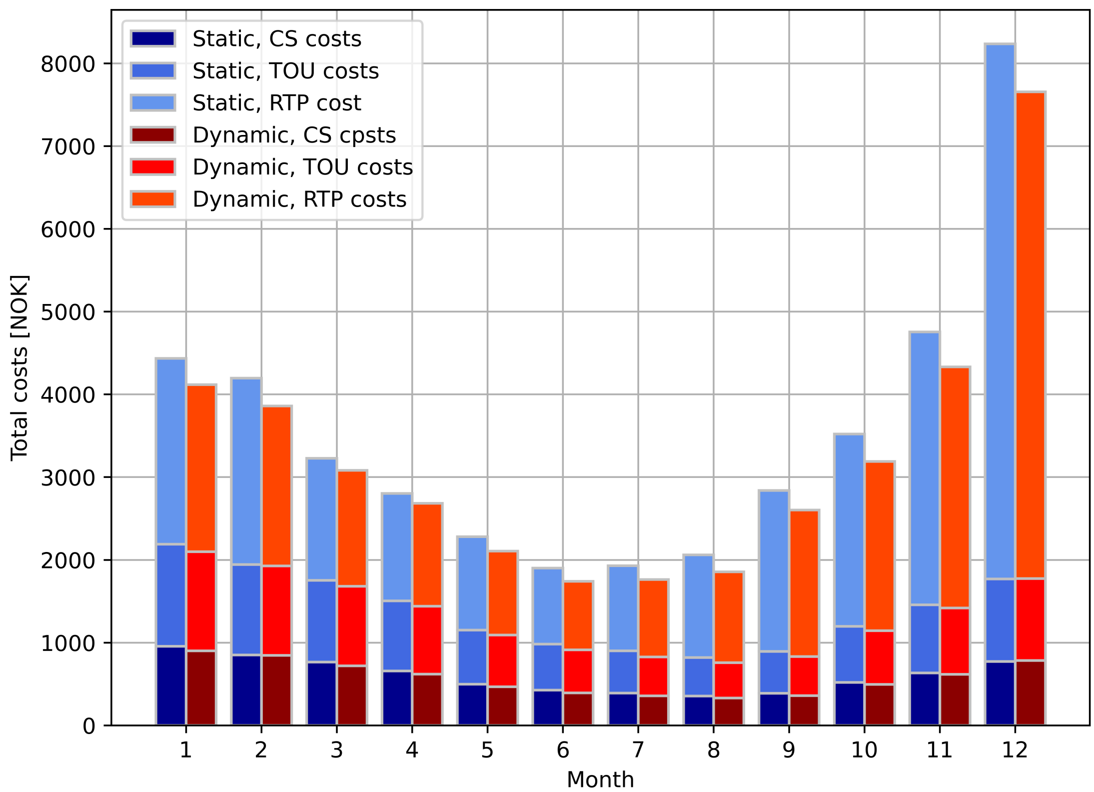

Figure 5.19: Total cost for each month, using dynamic operation of all assets compared to static operation

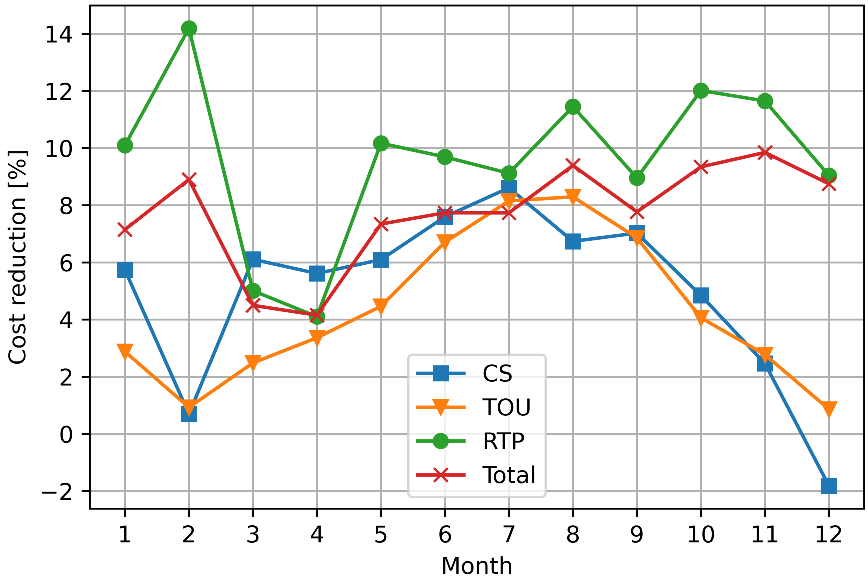

Figure 5.20: Cost reduction for each month, using dynamic operation of all assets compared to static operation

5.7 Further discussion

The reference case for the EV involves charging of the EV at full power when connecting to the house. This leads to higher loads and therefore higher costs due to CS. In addition, charging often coincide with the evening RTP peak, leading to further cost increases. This kind of charging pattern is highly unlikely to occur in a real word setting. Firstly, an electricity costumer on an RTP contract would be price sensitive since they have chosen the spot price contract over a flat volumetric contract. Secondly, an EV with an 85 kWh battery would not need charging every day, especially when the daily driving discharge is low. Finally, most modern EVs have the possibility to activate planned charging from the car's integrated system. That means the car can be set up to charge during the night regardless of plugin time, allowing the user to take advantage of the lower grid tariff even if no smart system is implemented.

When utilizing dynamic charging, the charging profile is optimized to limit cost through the different pricing mechanisms. Since there are no gains to be had by charging the EV more than necessary, the model mostly elects to charge to the lower SOC limit required for departure. The battery is thus kept at a relatively stable level, only charging around the same amount of energy as used during the daily commute, represented by the declining SOC. The battery SOC is kept at around 50% most of the time, a strategy that is beneficial for the longevity of the li-ion battery pack. According to a study [37], battery capacity retention after several thousand discharge cycles is higher if the battery is kept between 75-65%, and significantly lower if the battery is charged to 100%. Therefore, the operation of the battery is more optimal both in regard to short-term electricity cost, but also in regard to long-term operation of the vehicle, even though battery degradation is not simulated in his model.

Comparing the results of the individual asset operation against simultaneous asset operation reveals some interesting findings. Individually, EV and DHW resulted in yearly cost reductions of 5.7% and 2.5% respectively. In simultaneous operation, EV and DHW achieved a cost reduction of 7.08%, showing the compound effect of the assets. However, when adding the discharge capable assets of BESS and V2G, the cost reduction is 7.93%, which is only 0.85 percentage points increase from DHW add EV alone.

The CS tariff achieves its objective of facilitating demand response. The model consistently tries to maintain the grid load below the CS limit unless irregular price events occur, such that it becomes more optimal to charge up in preparation for the price peaks. If the overall goal of the DSO is to rebalance the grid loads and reduce price peaks, the CS tariff works well as a tool to rebalance the loads from the consuming assets such as DHW and EV. However, once assets with more flexibility potential are introduced, such as BESS and EV-V2H, the CS acts as a limiting factor in the flexibility potential. Such assets, especially when operating simultaneously, cause larger grid loads during the night. For the DSO, this is preferable to high day-time loads, since the grid is less congested. However, the CS limit inhibits the assets' flexibility by penalizing high grid loads regardless of the time of day. For flexible assets to fully take advantage of RTP differences, their use should not be limited, especially at night. A better grid tariff alternative could be a three step TOU, which could have a third and more expensive tariff during the hours of the peak load.

It is also evident that the gains from utilizing RTP differences is not always able to recuperate the efficiency losses of the battery charge-discharge cycle with the set efficiency. This study shows that the dischargeable assets only offered a limited benefit over the non-dischargeable assets, and only for periods with high price variations. Dischargeable assets are best suited to capturing the PV load that is generated during the middle of the day. This limits the BESSs utility in the winter, as the solar irradiation in winter is insufficient for generation of loads exceeding self-consumption, especially since the heating needs are higher in winter. This seasonal imbalance is something that short-term energy storage cannot address. In this configuration, the EV-V2H is less suited as an energy storage device for the residential household, since it is usually not connected to the house during daytime and thus unable to capture the PV load. However, the EV has a large battery pack, and is able to protect the household against occasional extreme price peaks trough V2H discharge. However, in the long run, the results of this simulation suggest that V2H operation has limited value compared to ordinary dynamic charging under a capacity subscription based tariff. The results also shows that the excess PV energy has flexibility potential in heating of DHW. For all the assets, the RTP scheme consistently provided the greatest cost reductions. EV and DHW offer flexibility in reacting to price variations and is thus able to generate long-term value.

5.7.1 Model limitations

The algorithm is built as separate Python files: one data file which contains initializes and updates the data for each iteration, one model file which contains the optimization model, and one main file that execute the algorithm. These files are available in the in Appendix A. It is also adaptable in the length of the scheduling and prediction horizons. It is however built for one day control horizons, and daily updates. The model can be run for any day and for any specified period, as long as the foundational datasets are available. Input parameters can be specified in the input file, and assets can be easily toggled on and off in the input file. However, the model is built for hourly resolutions and cannot easily be scaled to smaller resolutions. One disadvantage with the implementation of the rolling horizon approach is the optimization model itself has to be re-run for every CH with new input information. The PH forecast values must be recreated and resubmitted to the model. In this implementation, that consists of updating the input data dictionary, which adds to the computational execution time. This approach works for hourly resolutions, but for smaller resolutions such as minutes or seconds, the approach would scale poorly.

One drawback of the implemented method is lack of accuracy in the prediction horizon. Recall that forecasted loads and prices are comprised of the averages of the past week. This gives the model an indication of what to expect such that the decision input/output variables can be adjusted accordingly. In order to test the effectiveness of the chosen method for generating the prediction horizon, another simulation of all assets was conducted without prediction and relying entirely on deterministic data. It was found that the deterministic simulation yielded 0.5% reduction in cost compared to the situation with prediction, across the entire year.

Results also show that the variation in prices contribute to the profitability of dischargeable assets such as BESS and EV-V2H. However, when the prices are relatively stable, the efficiency losses can lead to increased cost compared to ordinary smart charging. Even though the optimization model is free to choose the optimal strategy for each iteration, it does not directly calculate the long term consequence of utilizing dischargeable assets. For each iteration, the optimization model only has information of the initial variable states and the prediction horizon ahead. If a discharge strategy is optimal over a non-discharge strategy for one iteration, it leaves the next iteration with a lower SOC. Since the new iteration has to be solved with updated information, it can lead to a different outcome than what the previous iteration anticipated. Over time, this strategy can lead to increased cost rather than reduced. This operation under uncertainty is a fundamental characteristic in rolling horizon approach. To solve this, a better price and load forecasting algorithm should be implemented in order to improve the strategy. Another possible solution could be to implement a function that measures the difference in peak and valley prices. If the difference is satisfactory, a constraint that governs whether discharge is allowed could be implemented.

6 Conclusion

In recent years, technological advancements have allowed energy consuming assets in Norwegian households to be managed in a more optimal manner. With the goal of facilitating demand response in households, financial incentives such as real time spot prices and grid tariffs dependent on time and capacity have been proposed. Using these price signals, this thesis has aimed to develop an optimization algorithm to investigate the optimal operation of flexible assets in a residential household.

To that end, a rolling horizon optimization model was created to solve a linear program governing the cost optimal operation of flexible assets. The model solved each day of 2021 in an iterative process, using the output variables as inputs for the next iteration. Several flexible assets were simulated and compared to their respective reference case, with a focus on the long-term value of operation. The simulated assets were an EV with bidirectional charging capabilities, a BESS and DHW. Assets were supplementary PV system. The asset's operational strategy was based on cost-optimality in response to an inelastic household demand load and long-term price signals. These signals were real time electricity prices and grid tariff, consisting of a combination of capacity subscription and time of use. The assets were simulated both separately and collectively to examine the value of flexible operation.

With the given electricity prices, grid tariff structure and household demand load, the BESS could yield 2% reduction in costs over a year compared to a reference case exporting the excess PV to the grid. DHW flexibility provided a 2.55% yearly cost reduction when the upper temperature limit was set to 90°C. Smart charging of the EV yielded a 5.7% reduction in cost, and 6.1% with bidirectional V2H charging enabled. However, some months yielded lower cost savings when V2H was enabled compared to ordinary smart charging. With the applied charge/discharge efficiency, high price variations are required in order for V2H to be profitable. In cases where the price is stable, a strategy of limiting grid interaction may be more prudent. In the case where all assets were present, yearly cost reductions of 7.93% were observed.

Cost reductions were decomposed to identify the individual contribution of each component to the total cost reduction. Of these components, the RTP cost reductions were the largest for most months. Periods with large spot price variations resulted in large reductions in RTP costs, while periods with stable prices resulted in low RTP cost reductions. However, the flexibility potential of the assets was limited by the CS load limit, which penalized high loads regardless of the time of day. Seasonal variations also impact the cost saving ability of the flexible assets. The summer months were characterized by high PV input and low household heating demand, which allowed for grater flexibility potential. This was especially evident for BESS and DHW, which were able to utilize the PV load to generate cost reductions. The EV and EV-V2G were more sensitive to changes in the electricity price.

The assets were able to reduce CS and TOU cost in most months. However, in situations with high prices, the model tended to prioritize high grid loads in price valleys in preparation of the price peaks. This resulted in lower CS cost reductions, and increased CS costs in some cases. Nevertheless, the total cost were reduced for all cases in all months of the year, illustrating the long-term value of optimal operation of flexible assets.

6.1 Future work

The model should be expanded with a better forecast algorithm for the predicted loads and prices. This could be an algorithm that compares historical weather and load data to extrapolate the predicted PV production and household demand load based on the weather forecast. Stochastic variables could also be implemented for the EV availability and DHW demand in order to better reflect real world use. In addition, a more accurate model of the EHW should be implemented such that the loads can be more accurately modeled. Additionally, other thermostatic loads could be added, such as heat pumps and radiators. This would increase the flexibility potential of the household. It could also be interesting to investigate the assets' behavior under different grid tariff schemes, such as measured peak tariff or a three stage TOU tariff.

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A Script implementation

A.1 Optimization model script

```python
from datetime import datetime , date, timedelta
import pyomo.environ as pyo
from pyomo.environ import value
from pyomo.opt import SolverFactory


def Optimization_model(Data, Bat_SOC,EV_SOC,DHW_temp, day):

    model = pyo.ConcreteModel()
    model.day = day
    """
    Sets
    """
    model.T = pyo.Set(initialize = Data["Op. Period data"]["hourlist for period"], ordered = True)  # Time steps for the model

    """
    Parameters
    """
    #Inflxeible Household load
    model.House_load = pyo.Param(model.T, initialize = Data["Op. Period data"]["Loads in period"])

    #Electricity price
    model.El_price = pyo.Param(model.T, initialize = Data["Op. Period data"]["Prices in period"])
```

```python

    """
    PV
    """
    if  Data["General"]["PV"] == True:
        model.PV_prod = pyo.Param(model.T, initialize = Data["Op. Period data"]["PV in period"])
    else:
        model.PV_prod = pyo.Param(model.T, initialize = 0)

    """
    Battery
    """
    if  Data["General"]["Battery"] == True:

        """Parameters"""
        Battery = Data["Battery"]
        model.Cap_Bat        = pyo.Param(initialize = Battery["Capacity"])   # Battery capacity [kWh]
        model.Q_max_ch_Bat   = pyo.Param(initialize = Battery["Q_max_ch"])   # maximum charging power [kW]
        model.Q_min_ch_Bat   = pyo.Param(initialize = Battery["Q_min_ch"])   # minimum charging power [kW]
        model.Q_max_dch_Bat = pyo.Param(initialize = Battery["Q_max_dch"])  # maximum discharging power [kW]
        model.Q_min_dch_Bat = pyo.Param(initialize = Battery["Q_min_dch"])  # minimum discharging power [kW]
        model.SOC_bat_max    = pyo.Param(initialize = Battery["Threshold_upper"])  # Lower state of charge threshold [kWh]
        model.SOC_bat_min    = pyo.Param(initialize = Battery["Threshold_low"])# Upper state of charge threshold  [kWh]
        model.eff_Bat        = pyo.Param(initialize = Battery["Charging_efficiency"])#

        model.initial_SOC_bat = Bat_SOC #uses SOC state from previous iteration as initial parameter

        """Variables"""
        model.SOC_bat = pyo.Var(model.T, within = pyo.NonNegativeReals, bounds = (model.SOC_bat_min,   model.SOC_bat_max))   # Battery State of charge variable
```

```
        model.Q_ch     = pyo.Var(model.T, within = pyo.NonNegativeReals, bounds = (model.Q_min_ch_Bat,  model.Q_max_ch_Bat))  # Battery power charging varliable
        model.Q_dch    = pyo.Var(model.T, within = pyo.NonNegativeReals, bounds = (model.Q_min_dch_Bat, model.Q_max_dch_Bat)) # Battery power discharge varliable

        model.Bat_eb_const = pyo.Constraint(model.T, rule = Bat_energy_balance)# puttting battery energy balace constraint into model

    else:
        model.Q_ch   = pyo.Param(model.T, initialize = 0)
        model.Q_dch  = pyo.Param(model.T, initialize = 0)
    """
    EV
    """
    EV_data = Data["EV"]

    model.Cap_EV     = pyo.Param(initialize = EV_data["Capacity"])
    model.eff_EV     = pyo.Param(initialize = EV_data["Charging_efficiency"])

    model.Dep_high   = pyo.Param(initialize = EV_data["Departure_high"])
    model.Dep_low    = pyo.Param(initialize = EV_data["Departure_low"])
    model.Deptime_EV =  pyo.Param(initialize = EV_data["EV Departure"])
    model.Arrivtime_EV =  pyo.Param(initialize = EV_data["EV Arrival"])
    model.EV_load    = pyo.Param(initialize = EV_data["Discharge when disconnected"])
    model.Q_max_EV   = pyo.Param(initialize = EV_data["Q_max"])
    model.Q_min_EV   = pyo.Param(initialize = EV_data["Q_min"])
    model.soc_max_EV = pyo.Param(initialize = EV_data["Threshold_upper"])
    model.soc_min_EV = pyo.Param(initialize = EV_data["Threshold_low"])
    model.Availability_EV = pyo.Param(model.T, mutable = True)

```

```
 model.inital_SoC_EV = EV_SOC #uses SOC state from previous iteration as initial parameter

 """lists"""

 model.EV_connected = list(range(len(Data["Op. Period data"]["hourlist for period"])))

 for t in model.EV_connected:
     if  model.Deptime_EV < t < model.Arrivtime_EV:
             model.EV_connected[t] = 0
     elif model.Deptime_EV+24 < t < model.Arrivtime_EV+24:
             model.EV_connected[t] = 0
     elif model.Deptime_EV+48 < t < model.Arrivtime_EV+48:
             model.EV_connected[t] = 0
     else:
         model.EV_connected[t] = 1

 """Variables"""
 model.SoC_EV = pyo.Var(model.T, within = pyo.NonNegativeReals, bounds = (model.soc_min_EV, model.soc_max_EV), initialize = EV_SOC )

 if  Data["General"]["EV"] == True:
     if Data["EV"]["Smart Charge"] == True:
         model.Q_ch_EV = pyo.Var(model.T, within = pyo.NonNegativeReals, bounds = (model.Q_min_EV, model.Q_max_EV))

         if Data["EV"]["VTG"] == True:
             model.Q_dch_EV = pyo.Var(model.T, within = pyo.NonNegativeReals, bounds = (model.Q_min_EV, model.Q_max_EV))
             model.EV_dischare_rule = pyo.Constraint(model.T, rule =discharge_limit)
         else:
             model.Q_dch_EV = pyo.Param(model.T, initialize = 0)

     else: #dumb charge
         model.Q_ch_EV = pyo.Param(model.T, initialize =Data["Op. Period data"]["EV in period"])
         model.Q_dch_EV = pyo.Param(model.T, initialize = 0)
```

```

        """Constraints"""
        model.EV_charge_req_const =   pyo.Constraint(model.T, rule = EV_Charge_requirement)
        model.EV_enery_balace_const =  pyo.Constraint(model.T, rule = EV_energy_balance)

    else:#No EV
        model.Q_ch_EV = pyo.Param(model.T, initialize = 0)
        model.Q_dch_EV = pyo.Param(model.T, initialize = 0)

    if  Data["General"]["DHW"] == True:
            DHW_data = Data["DHW"]
            model.inital_temp_DHW = DHW_temp

            model.Heat_Cap_DHW       = pyo.Param(initialize = DHW_data["Heat Capacity"])
            model.eff_DHW            = pyo.Param(initialize = DHW_data["efficiency"])
            model.DHW_max_load       = pyo.Param(initialize = DHW_data["Load"])
            model.DHW_loss           = pyo.Param(initialize = DHW_data["Loss"])
            model.min_temp_DHW       = pyo.Param(initialize = DHW_data["Min temp low dem"])
            model.morning_dem_start = pyo.Param(initialize = DHW_data["Morning demand start"])
            model.morning_dem_end    = pyo.Param(initialize = DHW_data["Morning demand end"])
            model.evening_dem_start   = pyo.Param(initialize = DHW_data["Evening demand start"])
            model.evening_dem_end    = pyo.Param(initialize = DHW_data["Evening demand end"])

            model.DHW_temp_demand    = pyo.Param(model.T, initialize =  Data["Op. Period data"]["DHW in period"])
            model.high_dem_min_temp_DHW = pyo.Param(initialize = DHW_data["Min temp high dem"])
            model.max_temp_DHW       = pyo.Param(initialize = DHW_data["Max temp"])

```

```
         model.Load_DHW    = pyo.Var(model.T, within = pyo.NonNegativeReals, bounds = (0, model.DHW_max_load))
         model.temp_DHW    = pyo.Var(model.T, within = pyo.NonNegativeReals, bounds = (model.min_temp_DHW, model.max_temp_DHW))
         model.temp_increase = pyo.Var(model.T)

         model.DWH_high_demand= list(range(len(Data["Op. Period data"]["hourlist for period"])))

         for t in model.DWH_high_demand:
             if  model.morning_dem_start < t < model.morning_dem_end or  model.evening_dem_start < t < model.evening_dem_end :
                     model.DWH_high_demand[t] = 1
             elif model.morning_dem_start+24 < t < model.morning_dem_end+24 or  model.evening_dem_start+24 < t < model.evening_dem_end+24 :
                     model.DWH_high_demand[t] = 1
             elif model.morning_dem_start+48 < t < model.morning_dem_end+48 or  model.evening_dem_start+48< t < model.evening_dem_end+48 :
                     model.DWH_high_demand[t] = 1
             else:
                     model.DWH_high_demand[t] = 0

         Data["DHW"]["High demand"] = model.DWH_high_demand

         model.DHW_temp_demand_const       = pyo.Constraint(model.T, rule = DHW_Temperature_demand)
         model.DHW_temp_regulation_const   = pyo.Constraint(model.T, rule = DHW_Temperature_regulation)
         model.DHW_temp_requirement_const  = pyo.Constraint(model.T, rule = DHW_Temperature_equirement)
 else:
     model.Load_DHW = pyo.Param(model.T, initialize = 0)
     model.temp_DHW = pyo.Param(model.T, initialize = 0)

 "Grid Tariff"

```

```
    model.VAT                    = pyo.Param( initialize = Data["Grid tariff"]["VAT"])
    model.tariff_day_summer    = pyo.Param( initialize =  Data["Grid tariff"]["S_Day"])
    model.tariff_night_summer = pyo.Param( initialize =  Data["Grid tariff"]["S_Night"])
    model.tariff_day_winter    = pyo.Param( initialize =  Data["Grid tariff"]["W_Day"])
    model.tariff_night_winter = pyo.Param( initialize =  Data["Grid tariff"]["W_Day"])
    model.CS_tariff              = pyo.Param( initialize =  Data["Grid tariff"]["CS limit"])

    #Variables for grid electricity and power flow into household
    model.grid_load = pyo.Var(model.T, within = pyo.NonNegativeReals)
    model.grid_export = pyo.Var(model.T, within = pyo.NonNegativeReals)


    model.hourtariff  = list(range(len(Data["Op. Period data"]["hourlist for period"])))#, within = pyo.NonNegativeReals)

    for t in model.hourtariff:
        if model.day.month > 2 or model.day.month < 10: #Summer (march - november)
            if 6 < t < 22 or model.day.weekday() > 4:
                model.hourtariff[t] = model.tariff_day_summer  # day or not weekend in "summer"
            else:
                model.hourtariff[t] = model.tariff_night_summer # night or weekend in "summer"
        else:  #Winter (april-oktober)
            if 6 < t < 22 or model.day.weekday() > 4:
                model.hourtariff[t] = model.tariff_day_winter#day or not weekend in "winter"
            else:
                model.hourtariff[t] =  model.tariff_night_winter #night or weekend in "winter"
```

```
    model.tariff_cost = pyo.Param( initialize =  Data["Grid tariff
"]["CS rate"])
    model.excess_cost = pyo.Param( initialize =  Data["Grid tariff
"]["Excess rate"])
    model.base_import_limit = pyo.Param( initialize =  Data["Grid
tariff"]["CS limit"])

    model.grid_import  = pyo.Var(model.T, within = pyo.
NonNegativeReals)
    model.base_import  = pyo.Var(model.T, within = pyo.
NonNegativeReals, bounds = (0, model.base_import_limit))
    model.extra_import = pyo.Var(model.T, within = pyo.
NonNegativeReals, bounds = (0, None))

    model.grid_import_const = pyo.Constraint(model.T, rule =
Grid_Import_Const)


    "Energy balance"

    model.EB_const = pyo.Constraint(model.T, rule = Energy_balance
) # puttting energy balace constraint into model

    '''
    Objective function
    '''
    model.obj = pyo.Objective(rule = Objective, sense = pyo.
minimize)
    opt = SolverFactory("gurobi_persistent")
    opt.set_instance(model)

    """
    Results
    """

    results = opt.solve()

    model.solutions.load_from(results)
    global Result
    Result = {}

```

```
    for v in model.component_objects(pyo.Var, active=True):
        Result[str(v)] = {}
        varobject = getattr(model, str(v))
        for index in varobject:
            Result[str(v)][index] = varobject[index].value


    Data["Result"][day] = Result
    peak_load             = max(Result["grid_load"].values())
    daily_TOU_cost        = sum((Result["grid_load"][t]   *model.hourtariff[t]for t in range(24)))
    daily_CS_base_cost    = sum((Result["base_import"][t] *model.tariff_cost  for t in range(24)))
    daily_CS_excess_cost  = sum((Result["extra_import"][t]*model.excess_cost  for t in range(24)))
    daily_export_gains    = sum((Result["grid_export"][t] *Data["Op. Period data"]["Prices in period"][t]/1000  for t in range(24)))
    daily_spotprice_cost  = sum((Result["grid_load"][t]   *Data["Op. Period data"]["Prices in period"][t]/1000  for t in range(24)))
    daily_houseload       = sum(Data["Op. Period data"]["Loads in period"][t]  for t in range(24))

    Result["PV"]={}
    if  Data["General"]["PV"] == True:
        daily_PV = sum(Data["Op. Period data"]["PV in period"][t] for t in range(24))
        for t in model.T:
            Result["PV"][t]=Data["Op. Period data"]["PV in period"][t]
    else:
        daily_PV = 0
        for t in model.T:
            Result["PV"][t]=0

    if  Data["General"]["DHW"] == True:
        daily_DHW_load= sum(Result["Load_DHW"][t]for t in range(24))
        final_DHW_temp = model.temp_DHW[23].value
    else:
```

```
        daily_DHW_load = 0
        final_DHW_temp = 0
        Result["Load_DHW"] = {}
        Result["temp_DHW"] = {}
        for t in model.T:
            Result["Load_DHW"][t]=0
            Result["temp_DHW"][t]=0

    if  Data["General"]["Battery"] == True:
        daily_BAT_ch = sum(Result["Q_ch"][t] for t in range(24))
        daily_BAT_dch = sum(Result["Q_dch"][t] for t in range(24))
        final_Bat_SOC = model.SOC_bat[23].value # final soc state to be used as input in next iteration
    else:
        daily_BAT_ch  = 0
        daily_BAT_dch = 0
        final_Bat_SOC = 0
        Result["Q_ch"] ={}
        Result["Q_dch"] ={}
        Result["SOC_bat"] ={}
        for t in model.T:
            Result["Q_ch"][t] = 0
            Result["Q_dch"][t] =0
            Result["SOC_bat"][t]=0

    if  Data["General"]["EV"] == True:

        if Data["EV"]["VTG"] == True:
            daily_EV_dch =  sum(Result["Q_dch_EV"][t] for t in range(24))
        else:
            Result["Q_dch_EV"] ={}
            for t in model.T:
                Result["Q_dch_EV"][t] =0
            daily_EV_dch  = 0
        if Data["EV"]["Smart Charge"] != True:
             Result["Q_ch_EV"] = {}
             for t in model.T:
                Result["Q_ch_EV"][t] = Data["Op. Period data"]["EV in period"][t]

```

```
     daily_EV_ch = sum(Result["Q_ch_EV"][t]for t in range(24))
     final_EV_SOC = model.SoC_EV[23].value

 else:
     daily_EV_ch = 0
     daily_EV_dch = 0
     final_EV_SOC = model.SoC_EV[23].value
     Result["Q_ch_EV"] = {}
     Result["Q_dch_EV"] = {}
     for t in model.T:
         Result["Q_ch_EV"][t] = 0
         Result["Q_dch_EV"][t] =0

 grid_import         = sum(Result["grid_load"][t]     for t in range(24))
 grid_base_import    = sum(Result["base_import"][t]   for t in range(24))
 grid_extra_import   = sum(Result["extra_import"][t] for t in range(24))
 grid_export         = sum(Result["grid_export"][t]   for t in range(24))

 """I/O"""
 Daily_Results       = {"peak_load":peak_load,
                       "daily_houseload":daily_houseload,
                       "daily_spotprice_cost":daily_spotprice_cost*model.VAT,
                       "total_costs":daily_spotprice_cost*model.VAT+daily_TOU_cost+daily_CS_base_cost+daily_CS_excess_cost-daily_export_gains,
                       "daily_CS_base_cost"   : daily_CS_base_cost,
                       "daily_CS_excess_cost" : daily_CS_excess_cost,
                       "daily_TOU_cost":daily_TOU_cost,
                       "daily_PV":daily_PV,
                       "daily_DHW_load":daily_DHW_load,
                       "daily_BAT_ch": daily_BAT_ch,
                       "daily_BAT_dch": daily_BAT_dch,
                       "daily_EV_ch":daily_EV_ch,
                       "daily_EV_dch":daily_EV_dch,
```

```
                                "grid_import":grid_import,
                                "grid_base_import":grid_base_import,
                                "grid_extra_import":grid_extra_import,
                                "grid_export":grid_export,
                                "daily_export_gains": daily_export_gains
    ,
                                "inital_SoC_EV":EV_SOC,
                                "initial_Bat_SOC:bat":Bat_SOC,
                                "inital_DHW_temp":DHW_temp,
                                "final_Bat_SOC ":final_Bat_SOC,
                                "final_EV_SOC":final_EV_SOC,
                                "final_DHW_temp":final_DHW_temp,
                                }
    return (Daily_Results,
            final_Bat_SOC ,
            final_EV_SOC,
            final_DHW_temp)  # extract model iteration results


"""
Constrains and expressions
"""

"""Grid tariff"""
def Base_Grid_Cost(model,t): #Determine the hourly cost of the CS
    base tariff component
    return model.grid_load[t]*model.tariff_cost

def Grid_Import_Const(model,t): #balance the base and excess cost
    agains the grid import
    return model.grid_load[t] == model.base_import[t] + model.
    extra_import[t]

def Penalty_cost(model,t): #Determine the hourly cost of the CS
    excess tariff component
    return model.extra_import[t]*model.excess_cost


def TOU_Tariff(model,t): # The Time-of-use component of the grid
    tariff
```

```
        if model.day.month > 2 or model.day.month < 10: #Summer (
    march - november)
            if 6 < t < 22 or model.day.weekday() > 4:
                model.hourtariff[t] = model.tariff_day_summer  #
    day or not weekend in "summer"
            else:
                model.hourtariff[t] = model.tariff_night_summer #
    night or weekend in "summer"
        else:  #Winter (april-oktober)
            if 6 < t < 22 or model.day.weekday() > 4:
                model.hourtariff[t] = model.tariff_day_winter#day
    or not weekend in "winter"
            else:
                model.hourtariff[t] =  model.tariff_night_winter
    #night or weekend in "winter"

        return model.hourtariff[t]

"""System"""
def Energy_balance(model,t):# defining energy balance equation:
    house load + battery charge = grid input + battery discharge +
    PV
    Input = model.grid_load[t]+ model.Q_dch[t] + model.PV_prod[t]
    + model.Q_dch_EV[t]# model inputs: grid load, battery discharge
     with efficeny and PV production
    Output = model.Q_ch[t] + model.House_load[t]+ model.
    grid_export[t] + model.Q_ch_EV[t] +model.Load_DHW[t]# model
    ouputs: battery charge with efficency and inflexible huse load
    return (Input == Output)

""" BESS"""
def Bat_energy_balance(model,t): # defining battery enegy balance
    if t == 0:
        return (model.SOC_bat[t]- model.initial_SOC_bat == model.
    Q_ch[t]*model.eff_Bat - model.Q_dch[t]/model.eff_Bat) # if t =
    0, use soc state from previus
    else:
        return (model.SOC_bat[t]- model.SOC_bat[t-1] == model.Q_ch
    [t]*model.eff_Bat - model.Q_dch[t]/model.eff_Bat)
```

```python
"""EV"""
def EV_energy_balance(model,t): #EV energy balace. Used ragardless of discharge is enabled
    if t == model.T.first():
        return(model.SoC_EV[t] - model.inital_SoC_EV == model.Q_ch_EV[t]*model.eff_EV*model.EV_connected[t]- model.Q_dch_EV[t]*model.EV_connected[t]/model.eff_EV - model.EV_load*(1-model.EV_connected[t]) )
    else:
        return(model.SoC_EV[t] - model.SoC_EV[model.T.prev(t)] == model.Q_ch_EV[t]*model.eff_EV*model.EV_connected[t] - model.Q_dch_EV[t]*model.EV_connected[t]/model.eff_EV- model.EV_load*(1-model.EV_connected[t]))

def discharge_limit(model,t): # Stops the model from discharging when not connected
    if model.EV_connected[t] == 0:
        return(model.Q_dch_EV[t] == 0)
    else:
        return(pyo.Constraint.Skip)

def EV_Charge_requirement(model,t): # Reqire the soc to be at at a certain capacity at departure time
    if t == model.Deptime_EV or t == model.Deptime_EV+24 or t == model.Deptime_EV+48:
        return model.SoC_EV[t] >= model.Dep_low
    else:
        return(pyo.Constraint.Skip)

"""DHW"""

def DHW_Temperature_demand(model, t): # Temperature discharge due to household water use
    if t == model.T.first():
        return(model.temp_DHW[t] - model.inital_temp_DHW   == model.temp_increase[t]  - model.DHW_temp_demand[t]  )
    else:
        return( model.temp_DHW[t] - model.temp_DHW[t-1]   == model.temp_increase[t]- model.DHW_temp_demand[t] )

```

```
def DHW_Temperature_regulation(model,t): # Electric load
    controlling the water temperaure
        return(model.Load_DHW[t] == model.Heat_Cap_DHW*(model.
    temp_increase[t]))#  + model.DHW_loss)

def DHW_Temperature_equirement(model,t): # Water temperature must
    be at a higer minimum level duruh high demand hours
    if model.DWH_high_demand[t] == 1:
        return model.temp_DHW[t] >= model.high_dem_min_temp_DHW
    else:
        return(pyo.Constraint.Skip)
"""
Objective function
"""

def Objective(model): # The objective is to minimize total cost of
     puchasing enegy from the grid
       Import = sum(model.grid_load[t]*model.El_price[t]/1000*
    model.VAT #RTP
                    + model.grid_load[t]*model.hourtariff[t]  #TOU
                    + Base_Grid_Cost(model,t) #Base CS
                    + Penalty_cost(model,t) #Excess CS
                   for t in model.T)

       Export = sum(model.grid_export[t]*model.El_price[t]/1000
    for t in model.T)

       return (Import - Export)
```

Listing A.1: Data initialization

A.2 Main algorithm

```python


from datetime import datetime, time, date, timedelta
import pandas as pd
import numpy as np
import calendar
import Initialize as init # Data initialization and updating scipt
import Optimization_model as opt # optimzation model script
import matplotlib.pyplot as plt


def _main_(): #main function
    start = datetime.now() #use to see script runtime
    print("Script started ",start )
    global Data, Yearly_Results

    Data = init.Intial_Data_dict()  #Run the Data dict for the first time for model input
    print("Initialiization comlete",datetime.now() )
    print("Preamble complete", datetime.now() - start)

    monthrange = range(1,13 ) # for each month (1 to start at january, 13 to include december)
    initial_day = date(2021,1,1)

    Yearly_Results = runmodel(Data,initial_day,monthrange,)#Runs the model for each month in the specifed month range

    print("Script execution time", datetime.now() - start) # examine toal runtime


def runmodel(Data,initial_day,monthrange):

    """initialization"""
    if  Data["General"]["Battery"] == True:
        Bat_SOC = Data["Battery"]["Inital SOC"]
    else:
```

```
        Bat_SOC = 0
    if Data["General"]["EV"] == True:
        EV_SOC  = Data["EV"]["Inital SOC"]
    else:
        EV_SOC = 0
    if Data["General"]["DHW"] == True:
        DHW_temp= Data["DHW"]["Inital temp"]
    else:
        DHW_temp=  0

    Yearly_Results ={}


    """Run for the Scheduling Horizon"""

    for month in monthrange: #Runs for each month,
        monthname = calendar.month_name[month]
        monthlength  = calendar.monthrange(initial_day.year,initial_day.month)[1] # integer - lenght in days of current month

        Data["General"]["Scheduling Horizon"] = monthlength
        N = Data["General"]["Prediction Horizon"]

        Data["General"]["Prediction Horizon"] = N # restore the model horizon after horizon reduction
        Data["Daily Result"] ={}
        day = initial_day
        Daily_Results = {}

        """ Day Run """
        for i in range(1,Data["General"]["Scheduling Horizon"]+1): #run for each day in the sheduling horizon  (month)

            Data = init.Update_Data_dict(Data,day)# Update Data dict

            (Daily_Results[day],
            final_Bat_SOC ,
            final_EV_SOC,
            final_DHW_temp,
```

```
            )= opt.Optimization_model(Data, Bat_SOC,EV_SOC, DHW_temp, day) # Run model, extract results


            Yearly_Results[day] = Daily_Results[day]



            """Prepare next iteration"""

            day      += timedelta(days = 1) # prepare for running for the next day
            Bat_SOC  = final_Bat_SOC
            EV_SOC   = final_EV_SOC
            DHW_temp = final_DHW_temp

            """ Horizon Reduction"""# For horizon reduction at the end of the month

            horizon_reduction(Data, day)

            """End of day run """


        initial_day = initial_day + timedelta(days =monthlength)
        """"End of Month Run """
    return Yearly_Results

def horizon_reduction(Data, day): #This function reduces the prediction horizon when  the end of the shedulcing horizon is about to be reached
    horizon_last_day = day + timedelta(hours=len(Data["Op. Period data"]["hourlist for period"])) # Finds the last day of the predicion horizon
    while day.month != horizon_last_day.month and len(Data["Op. Period data"]["hourlist for period"]) > 24: #if the last day of the horizon is in a different month than current month, reduce the horizon, expept if the horizon is
        horizon_last_day = day + timedelta(hours=len(Data["Op. Period data"]["hourlist for period"]))
        h = Data["General"]["Prediction Horizon"]
```

```
        Data["General"]["Prediction Horizon"] = h-1 #reduce number
    of days with 1  for each while iteration
        init.Update_Data_dict(Data,day) # update the dict with new
    data, rund the while condition again to check

_main_()
```

Listing A.2: Data initialization

A.3 Initialization

```python
import pandas as pd
from datetime import *
import calendar

def read_PVdata(Data): #reads a file from renewables ninja to dict form
    filename = Data["General"]["PV file"]
    d_parser = lambda x: datetime.strptime(x,"%Y-%m-%d %H:%M") + timedelta(731)
    pvdata = pd.read_csv(filename,
                         skiprows = 3,
                         usecols = ["local_time", "electricity"],
                         index_col= ["local_time"],
                         parse_dates=["local_time"],
                         date_parser = d_parser,
                         dtype={"electricity":"float64"},
                         )

    pvdata["electricity"]=pvdata["electricity"]*Data["PV"]["Installed PV capacity [kWh]"] # Scaling the base data (1kW) with installed capcity [kWh]
    pvdatadict = pvdata.to_dict() #convert to dict
    return pvdatadict["electricity"]# drops parent dict


def read_electric_load(Data):
    filename = Data["General"]["load file"]
    electric_load= pd.read_csv(filename,
                        usecols=["KWH 60 Forbruk","Fra"],
                        index_col= ["Fra"],
                        parse_dates=["Fra"],
                        #dtype={"KWH 60 Forbruk":"float64"},
                        #decimal=',',
                        #date_parser = d_parser
                        ).to_dict()
    return electric_load["KWH 60 Forbruk"]

```

```
def read_elspot_price(Data): #This function assumes a NordPool price file
   # NB! Nordpool files are sometimes corrupt and unreadable!
    filename = Data["General"]["Prices file"]
    place = 12 #Select coloum for price region. Example Bergen = 12", trondheim = 14
    d_parser = lambda x: datetime.strptime(x,"%Y-%m-%d %H:%M:%S")
    elspotprice = pd.read_excel(filename,
                                usecols=[0,1,place],
                                skiprows=2,
                                parse_dates=["Date"],
                                date_parser = d_parser,
                                names=["Date","Hours","Elspot Prices in NOK/MWh"])
    elspotprice.set_index(["Date"], drop = False, inplace = True)
    for i in range(len(elspotprice)): # fix the timedates so date and hour is combined
        hours = elspotprice["Hours"][i]
        pd.options.mode.chained_assignment = None
        elspotprice["Date"][i] = elspotprice["Date"][i] + timedelta(hours = int(hours[:2]))
    elspotprice = elspotprice.to_dict()
    return elspotprice["Elspot Prices in NOK/MWh"]

def read_dumb_DHW():
    filename = Data["General"]["DHW file"]
    DHW_Weekday         = pd.read_excel(filename,sheet_name ="Data",usecols=[3]).to_dict()
    DHW_Weekend         = pd.read_excel(filename,sheet_name ="Data",usecols=[4]).to_dict()
    DHW_standby         = pd.read_excel(filename,sheet_name ="Data",usecols=[5]).to_dict()
    dumb_load_weekday   = pd.read_excel(filename,sheet_name ="Data",usecols=[0]).to_dict()
    dumb_load_weekend   = pd.read_excel(filename,sheet_name ="Data",usecols=[1]).to_dict()

    DHW ={"Weekday":DHW_Weekday["Temp Ukedag [C]"],
          "Weekend":DHW_Weekend["Temp helg [C]"],
          "Standby":DHW_standby["Standby"],
          "dumb_load_weekday": dumb_load_weekday["Ukedag"],
```

```
            "dumb_load_weekend": dumb_load_weekend["Helg"],}
    return DHW

def daily_dumb_EV_load(Data):
    cap = Data["EV"]["Capacity"]
    arr = int(Data["EV"]["EV Arrival"])
    dep = Data["EV"]["EV Departure"]
    D   = Data["EV"]["Discharge when disconnected"]
    Q   = Data["EV"]["Q_max"]
    eff = Data["EV"]["Charging_efficiency"]
    dur = arr-dep
    SOC_ar = cap-dur*D
    charge_duration= (cap - SOC_ar)/(Q*eff)
    charge_duration_int= int((cap - SOC_ar)//(Q*eff))
    rem=charge_duration-charge_duration_int
    EV_loadlst = []
    for i in range(24):#intialize load list
        EV_loadlst.append(0)
    for i in range(charge_duration_int+1):
        if i < charge_duration_int:
            E = Q   #charge at full power untill the last hour
        else:
            E =Q*rem  #charge at remaining power
        EV_loadlst[arr+i] = E
    Data["EV"]["Daily EV load"] = sum(EV_loadlst)
    return EV_loadlst


def Daily_load(day,electric_load): # returns a list of loads in a 24h period for any valid day
    Daily_Load_list = []
    for key in electric_load.keys():
        if day == key.date():
          Daily_Load_list.append(electric_load[key])
    while len(Daily_Load_list) != 24: # in case there is something missing in the data
        Daily_Load_list.append(0)
        Data["Deviations"] = {day:f"Load list appenend hour {len(Daily_Load_list)+1}"}
    return Daily_Load_list

```

```
def Daily_price(day,elspot_price): # returns a list of prices in a 24h period for any valid day
    Price_list = []
    for key in elspot_price.keys():
        if day == key.date():
            Price_list.append(elspot_price[key])
    while len(Price_list) != 24:# in case there is something missing in the data
        Price_list.append(0)
        Data["Deviations"] = {day:f"Price list appenend hour {len(Price_list)+1}"}
    return Price_list

def Daily_PV(day,pvdata): # returns a list of PV load injections in a 24h period for any valid day
    PV_list = []
    for key in pvdata.keys():
        if day == key.date():
            PV_list.append(pvdata[key])
    while len(PV_list) != 24:# in case there is something missing in the data
        PV_list.append(0)
        Data["Deviations"] = {day:f"PV list appenend hour {len(PV_list)+1}"}
    return PV_list

def Daily_DHW_load(day,Data):
    DHW_list = []
    if Data["General"]["Dumb DHW"]==True:
        if day.weekday() < 5:
            DHW_list = list(Data["Yearly data"]["DHW"]["dumb_load_weekday"].values())
        else:
            DHW_list = list( Data["Yearly data"]["DHW"]["dumb_load_weekend"].values())
        return DHW_list

    else:
        if day.weekday() < 5:
            DHW_list = list(Data["Yearly data"]["DHW"]["Weekday"].values())
```

```
        else:
            DHW_list = list( Data["Yearly data"]["DHW"]["Weekend"].values())
        return DHW_list

def Intial_Data_dict(): # Creates the data dict
    global Data
    Data ={} # create master dicionary
    filename = "Inputs.xlsx" #define filename
    General =  pd.read_excel(filename, sheet_name = "General", usecols = 'A:B')

    Data["Yearly data"]={}

    General.set_index("Variable", drop=True, inplace=True)
    General = General.to_dict()
    Data["General"] = General["Value"]#Variabel and value are headers used to sort the indexing. Its is then dropped from the dict
    Data["General"]["Initial day"] = Data["General"]["Initial day"].date()

    GT = pd.read_excel(filename, sheet_name = "Grid tariff", usecols = 'A:B')
    GT.set_index("Variable", drop=True, inplace=True)
    GT=GT.to_dict()
    Data["Grid tariff"] = GT["Value"]

    #if Data["General"]["EV"] == True:
    EV = pd.read_excel(filename, sheet_name = "EV", usecols = 'A:B')
    EV.set_index("Variable", drop=True, inplace=True) # fix indexing
    EV = EV.to_dict()# turn dataframe to dict
    Data["EV"] = EV["Value"]

    Data["EV" ]["Threshold_low"]   = Data["EV" ]["Threshold_low"]*Data["EV" ]["Capacity"] #Set Battery limits according to specified nuber of batteries
    Data["EV" ]["Threshold_upper"] = Data["EV" ]["Threshold_upper"]*Data["EV" ]["Capacity"]
```

```
    Data["EV" ]["Departure_high"]  = Data["EV" ]["Departure_high" ]*Data["EV" ]["Capacity"]
    Data["EV" ]["Departure_low"]   = Data["EV" ]["Departure_low"]*Data["EV" ]["Capacity"]
    Data["EV" ]["Start_end_soc"]   = Data["EV" ]["Start_end_soc"]*Data["EV" ]["Capacity"]

    Battery  = pd.read_excel(filename, sheet_name = "Battery", usecols = 'A:B') #imports exel sheet in a dataframe
    Battery.set_index("Variable", drop=True, inplace=True) # fix indexing
    Battery = Battery.to_dict()# turn dataframe to dict
    Data["Battery"] = Battery["Value"]

    Data["Battery" ]["Capacity"] = Data["Battery" ]["Capacity"]*Data["Battery"]["Number of batteries"] #Set capacity according to specified nuber of batteries
    Data["Battery" ]["Threshold_low"] = Data["Battery" ]["Threshold_low"]*Data["Battery" ]["Capacity"] #Set Battery limits according to specified nuber of batteries
    Data["Battery" ]["Threshold_upper"] = Data["Battery" ]["Threshold_upper"]*Data["Battery" ]["Capacity"]

    DHW = pd.read_excel(filename, sheet_name = "DHW", usecols = 'A:B')
    DHW.set_index("Variable", drop=True, inplace=True) # fix indexing
    DHW = DHW.to_dict()# turn dataframe to dict
    Data["DHW"] = DHW["Value"]
    Data["Yearly data"]["DHW"]= read_dumb_DHW()


    Data["Yearly data"]["elspot price"] = read_elspot_price(Data)
    Data["Yearly data"]["electric load"] = read_electric_load(Data)

    PV = pd.read_excel(filename, sheet_name = "PV", usecols = 'A:B')
    PV.set_index("Variable", drop=True, inplace=True) # fix indexing
    PV = PV.to_dict()# turn dataframe to dict
```

```
    Data["PV"] = PV["Value"]
    Data["Yearly data"]["PV data"]= read_PVdata(Data)

    Data["Result"] ={}


    return  Data

def Update_Data_dict(Data,day): # updates the data dict
    N = Data["General"]["Prediction Horizon"]

    days =[]
    for i in range(N):
        days.append(day+ timedelta(days=i)) # list of days in model horizon

    Data["Op. Period data"] = {}
    Data["Op. Period data"]["hourlist for period"] = list(range(N*24))

    temp_Load_list = []
    temp_Price_list= []
    temp_PV_list = []
    temp_DHW_list =[]
    temp_EV_list =[]
    Load_list   = []
    Price_list = []
    Pv_list = []
    DHW_list =[]
    EV_list =[]

    if Data["General"]["Prediction"]==True and day >  date(2021,1,7):

        d = day
        load_lst =[]
        price_lst=[]
        average_load=[]
        average_price= []

        for i in range(7):# get average values for the last 7 days
```

```
            d = day - timedelta(days=7-i)
            price_lst.append(Daily_price(d, Data["Yearly data"]["elspot price"]))
            load_lst.append(Daily_load(d,   Data["Yearly data"]["electric load"]))
        for hour in range(24):
            average_price.append(sum(price_lst[day][hour] for day in range(7))/7)
            average_load.append(sum(load_lst[day][hour] for day in range(7))/7)

        for i in range(N):
            if i == 0:
                temp_Load_list.append(Daily_load(days[i],   Data["Yearly data"]["electric load"]))
                temp_Price_list.append(Daily_price(days[i], Data["Yearly data"]["elspot price"]))
            else:
                temp_Load_list.append(average_load)
                temp_Price_list.append(average_price)

    else:
       for i in range(N):  #Creates a list of list. Needs to be reduced to a single list. Probably a better way to do this
           temp_Load_list.append(Daily_load(days[i],   Data["Yearly data"]["electric load"]))
           temp_Price_list.append(Daily_price(days[i], Data["Yearly data"]["elspot price"]))

    for i in range(N): #Creates values for operating period
            Load_list   += temp_Load_list[i]
            Price_list  += temp_Price_list[i]

    Data["Op. Period data"]["Prices in period"]=  {}
    Data["Op. Period data"]["Loads in period"] = {}

    if "PV data" in Data["Yearly data"]:
        for i in range(N):
            temp_PV_list.append(Daily_PV(days[i],Data["Yearly data"]["PV data"]))
            Pv_list += temp_PV_list[i]
```

```
        Data["Op. Period data"]["PV in period"] = {}

    if "DHW" in Data:
        for i in range(N):
            temp_DHW_list.append(Daily_DHW_load(days[i],Data))
            DHW_list +=  temp_DHW_list[i]
        Data["Op. Period data"]["DHW in period"] = {}

    if "EV" in Data:
        for i in range(N):
            temp_EV_list.append(daily_dumb_EV_load(Data))
            EV_list +=  temp_EV_list[i]
        Data["Op. Period data"]["EV in period"] = {}

    for i in Data["Op. Period data"]["hourlist for period"]: # add values to data dict
      Data["Op. Period data"]["Loads in period"][i]   = Load_list[i]
      Data["Op. Period data"]["Prices in period"][i]  = Price_list[i]
      if "PV in period" in  Data["Op. Period data"]:
          Data["Op. Period data"]["PV in period"][i]  = Pv_list[i]
      if "DHW in period" in  Data["Op. Period data"]:
          Data["Op. Period data"]["DHW in period"][i] = DHW_list[i]
      if "EV in period" in  Data["Op. Period data"]:
          Data["Op. Period data"]["EV in period"][i]  = EV_list[i]

    if Data["General"]["Dumb DHW"]==True: # if dumb DHW, add to load

        for key in Data["Op. Period data"]["Loads in period"].keys():
           Data["Op. Period data"]["Loads in period"][key] = Data["Op. Period data"]["Loads in period"][key]+Data["Op. Period data"]["DHW in period"][key]

    if Data["General"]["Dumb EV"]==True: #if dumb EV, add to load

        for key in Data["Op. Period data"]["Loads in period"].keys():
```

```
                Data["Op. Period data"]["Loads in period"][key] = Data["Op. Period data"]["Loads in period"][key]+Data["Op. Period data"]["EV in period"][key]

    return Data
```

Listing A.3: Data initialization

NTNU

Norwegian University of
Science and Technology