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MODEL PREDICTIVE CONTROL FOR BATTERY MANAGEMENT SYSTEM IN RESIDENTIAL APPLICATION

Master's thesis

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MUDELIPÕHINE JUHTIMINE AKU HALDUSSÜSTEEMILE KODUKASUTUSES

Magistritöö

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Author’s declaration of originality

I hereby certify that I am the sole author of this thesis. All the used materials, references to the literature and the work of others have been referred to. This thesis has not been presented for examination anywhere else.

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Abstract

In the evolving field of residential energy management, optimizing energy use while minimizing costs has become increasingly critical. This thesis focuses on optimizing home energy systems using Model Predictive Control (MPC) to enhance economic efficiency and battery longevity. The integration of market prices, historical energy demand, and solar production data into the MPC algorithm allows for predictive, dynamic management of energy storage.

The research investigates how various operational parameters influence the economic efficiency of home energy systems, explores robust responses to disturbances, and assesses the performance of simplified versus complex system configurations. By developing an algorithm that intelligently manages battery charge and discharge cycles, the thesis aims to minimize electricity costs while considering the operational life of the battery.

This system provides homeowners with predictive data on savings and energy management, promoting informed decisions on future investments in PV and battery systems while having minimal interface with user, requiring only potential PV panel and battery configuration with historical electricity demand data.

This thesis is written in English and is 55 pages long, including 5 chapters, 13 figures and 4 tables.

Annotatsioon

MUDELIPÕHINE JUHTIMINE AKU HALDUSSÜSTEEMILE KODUKASUTUSES

Elamuenergeetika haldamise valdkond areneb pidevalt ning energiakasutuse optimeerimine ja kulude vähendamine on muutunud üha olulisemaks. Käesolev lõputöö keskendub koduste energiasüsteemide tõhustamisele, kasutades selleks mudelipõhist ennustavat juhtimist (inglise keelse *model predictiv control* - MPC), et parandada süsteemi majanduslikku tõhusust ja pikendada akude eluiga. börsihinna, ajaloolise energianõudluse ja päikeseenergia tootmisandmete kaasamine MPC algoritmi võimaldab energiasalvestuse proaktiivset ja dünaamilist juhtimist.

Võrreldakse, kuidas erinevad operatiivsed parameetrid mõjutavad koduste energiasüsteemide majanduslikku efektiivsust, analüüsib süsteemi vastupidavust häiretele ja võrdleb lihtsate ning keerukate süsteemilahenduste toimivust. Lõputöö töötab välja algoritmi, mis reguleerib akude laadimis- ja tühjendamistsükleid, eesmärgiga vähendada elektri arvet.

Väljatöötatud süsteem pakub koduomanikele infot, milline võiks olla sobilik päikesepaneelide ja akude kombinatsioon, ning anda hinnangu kui palju võiks potentsiaalne süsteem elektriarvet vähendada. Süsteemi kasutamine on tehtud kasutajasõbralikus, kastutades ainult koduomaniku viimase aasta elektri tarbimise andmeid.

Lõputöö on kirjutatud inglise keeles ning sisaldab teksti 55 leheküljel, 5 peatükki, 13 joonist, 4 tabelit.

List of abbreviations and terms

ESS	Energy storage system
EV	Electric vehicle
IoT	Internet of Things
PV	Photovoltaic
MPC	Model predictive control
SOC	State of charge
kWh	Kilowatt-hour
Ah	Ampere-hour
nZEB	Nearly zero-emission building

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1 Introduction

The deployment of photovoltaic (PV) systems in residential settings has become increasingly popular as a means of reducing household energy expenses and contributing to environmental sustainability. This trend is supported by significant advancements in solar panel efficiency and a reduction in installation costs over recent years [1]. In response to the limitations in daily sunlight hours and the variability of solar production, many homeowners are integrating battery storage systems with their PV installations. This approach allows for the storage of excess electricity generated during peak production times, which can then be used during periods of low production or high demand, like nighttime.

The strategic addition of battery storage not only maximizes the utility of generated solar power but also provides a buffer against grid dependency and electricity price fluctuations. Another aspect of technological integration in this field is the use of historical energy consumption data, which allows for predictive analysis and more accurate sizing of both PV installations and storage capacities. By managing the charge and discharge cycles through a Model Predictive Control (MPC) algorithm that accounts for historical consumption patterns, it is possible to reduce cost of the electricity and increase overall system efficiency.

1.1 Research questions

The utilization of MPC algorithm in residential energy management systems offers a sophisticated approach to optimizing home energy use. By integrating real-time market prices, the MPC can make timely decisions to minimize costs. Moreover, the inclusion of detailed historical and solar production data enhances the algorithm's ability to forecast energy needs accurately, which is crucial for efficient energy storage and consumption. Simultaneously, strategic management of battery charging and discharging not only supports system efficiency but also extends the operational lifespan of the battery systems, presenting a dual benefit. These research questions aim to explore the efficacy of these integrations and their impact on the sustainability and cost-effectiveness of home energy systems.

While the problem of minimizing electricity bill is complex in its nature, this thesis is simplifying the problem by using hourly home electricity demand data that is measured grid operator and is easily accessible with generating PV production profiles that could be used to configure different residential building setups and approximate the electricity cost reduction. In this thesis, our goal is to investigate:

- How does the integration of various operational parameters (like SoC, PV production, market price etc) into the MPC algorithm enhance the economic efficiency of home energy systems?
- How to respond to disturbances that are not modelled into the prediction to achieve robust MPC?
- Can simplified solution be used to give numerical approximation on how different system configurations (PV panels count and battery size) perform and how does it compare to more complex solutions?

1.2 Goal

The primary aim of this thesis is to develop an algorithm capable of minimizing electricity costs through intelligent battery charge and discharge cycles, while also considering the extension of the battery's operational life. Homeowners can input specific parameters, such as historical electricity usage (that can be easily download form Elering’s webpage) and the physical capacities of their PV and battery systems. The MPC algorithm developed here integrates these inputs with additional data on solar production trends and real-time electricity market prices specific to Estonia.
This approach allows the system to predict optimal periods for energy storage and consumption, thereby maximizing cost savings and enhancing energy efficiency. Furthermore, by providing users with predicted savings and detailed energy management recommendations, the system also helps in making informed decisions about future investments in PV and battery systems. Overall, the goal is to offer a tool that not only optimizes financial returns but also contributes to the sustainability of home energy systems by reducing waste and improving the balance between energy production and consumption.

Bigger goal of this thesis is to incorporate developed system into nearly zero-emission building (nZEB) that is use for research purposes in TalTech to make residential building more efficient and financially feasible in future. The project involves custom electronics components to improve the efficiency of the whole building, This thesis focus primarily on the high level control optimization problem, solving problem in energy management unit shown in Figure 1.

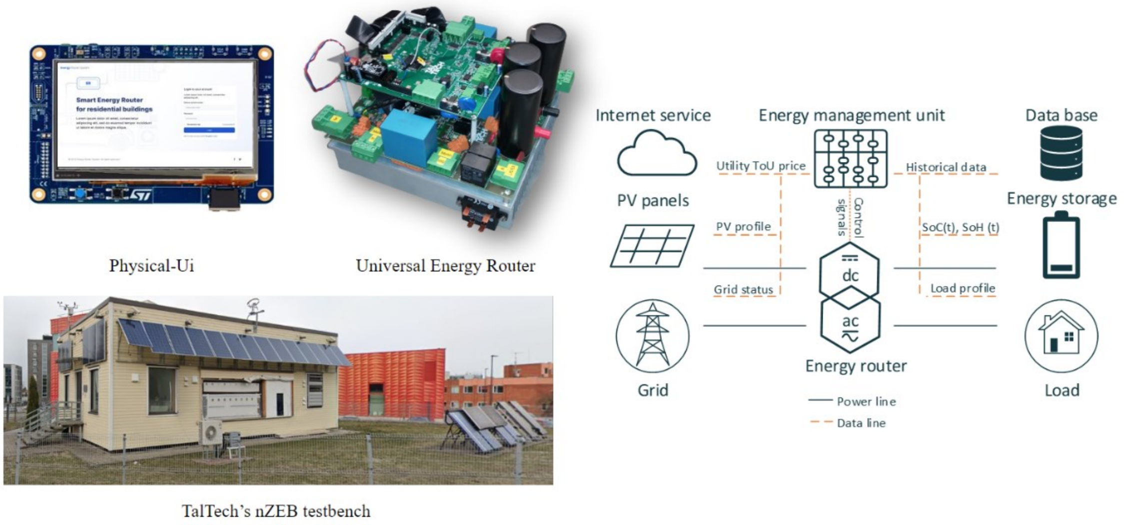

Figure 1 Overview of TalTech's nZEB system. [17]

1.3 Literature overview

Finding optimal control commands for any given system is well researched topic and has many subfields spanning between linear and non-linear systems with different approaches involving searching through the entire state space or using some methods that iteratively move closer to the optimal solution. MPC has stood out in recent years because its ability to consider constraints while still handling nonlinear dynamics of the system.

In the energy domain there are a lot of research already done and there are also good review articles [2] described pros and cons of different approaches and what are their limitations. According to the [2], there are classical optimisation techniques, which involve linear and dynamic programming where simpler problems can be solved because most of the real world problems are non-linear and in case of dynamic programming searching through all of the feasible solution is very expensive and slow. In addition, there are nonlinear and stochastic control strategies where model predictive control is used very extensively because the cost function can be tuned so that it will consider uncertainty of the system and still won't exceed any constraints as is done in vehicle control [3] [4] [5]. Another review paper [6] is focusing on buildings, minimizing the cost, greenhouse gas emissions while still not violating user comfort and considering uncertainties in the system.

With a rise of different machine learning methods and success in other fields like image recognition and large language models, the energy domain is using machine learning enchant the electricity production and demand profiles while giving uncertainty metrics that could be used during control cycle [7]. There are also experiments with other energy storage devices like super- and ultracapacitors. [8]

As can be seen there is a lot of work already done in the field, but they require a lot of knowledge about the building, predictive models, and a lot of them are not tested in the real world, sticking to only simulation as carrying out real world tests are hard and expensive. To give residential building owner better understanding on how their home might benefit from PV panel arrays and batteries that are controlled optimally to minimize the electricity bill, much simpler systems can be used.

	Advantages	Disadvantages
MPC	• Predictive and adaptive, handling constraints effectively. • Optimizes future performance, predicting and reacting to variables.	• Computationally intensive, requiring powerful processors. • Complex to implement, needing accurate models.
Dynamic programming	• Handles multi-stage decision processes well. • Effective for problems with stochastic elements.	• "Curse of dimensionality"; scales poorly with increased states. • Requires complete model of the environment.

Reinforcement Learning	• Learns from environment through trial and error. • Adapts to changes in the operational environment.	• Requires significant amount of data and training. • May converge slowly or to suboptimal solutions.

2 Methodology

This chapter outlines the data collection and preparation processes for a thesis on energy management systems, emphasizing the use of PV production data, household electricity demand, and market prices in Estonia. The data, recorded hourly, allows to analysis of energy consumption and production patterns. Techniques for data normalization and integration are discussed to ensure accuracy and consistency across different datasets. Additionally, the chapter introduces the application of MPC techniques, focusing on optimizing the economic efficiency and longevity of home energy management systems.

2.1 Data Collection and Preparation

The foundation of any robust energy management system lies in the quality and granularity of the data used. For this thesis, PV production, household electricity demand, and electricity market prices in Estonia are used. The primary data sources included a summary of yearly PV production in Estonia, recorded hourly in kilowatt-hours (kWh), and similarly structured data for home electricity demand. This allowed for a detailed comparison and analysis on an hourly basis, providing a fine-grained view of energy dynamics.

Market price data for electricity, essential for calculating potential cost savings, was obtained from Elering’s official website, which provides comprehensive energy market statistics for Estonia. This dataset was crucial for aligning energy usage and production with market dynamics, enabling more precise financial analyses.

To address the variability in PV production across different regions and conditions, the data was transformed by converting the absolute production figures into percentages. This method facilitated the estimation of energy production for any given PV installation size, based on typical production patterns observed throughout the year in Estonia. While this approach averages out anomalies due to weather variations, such as cloudy days, it provides a reliable baseline from which users can manually adjust predictions to reflect more extreme weather scenarios.

The data integration process involved aligning all datasets by datetime, ensuring that each hour's data from different sources corresponded accurately. Data cleaning was another critical step, involving the removal of duplicates (such as those caused by daylight saving time adjustments) and the filling of missing values with data from the previous week. This method proved adequate for the scope of this study, where not all data was used continuously but selected periodically for specific simulations.

The sample electricity demand for home was also obtained from Elektrilevi's homepage [9] and authors home data was used. This data might slightly deviate from the typical demand profile as there are 2 people working from home and there is no smart HVAC system that would consider the temperature of the rooms or the market price. In addition, the primary heating is provided by wood oven heating.

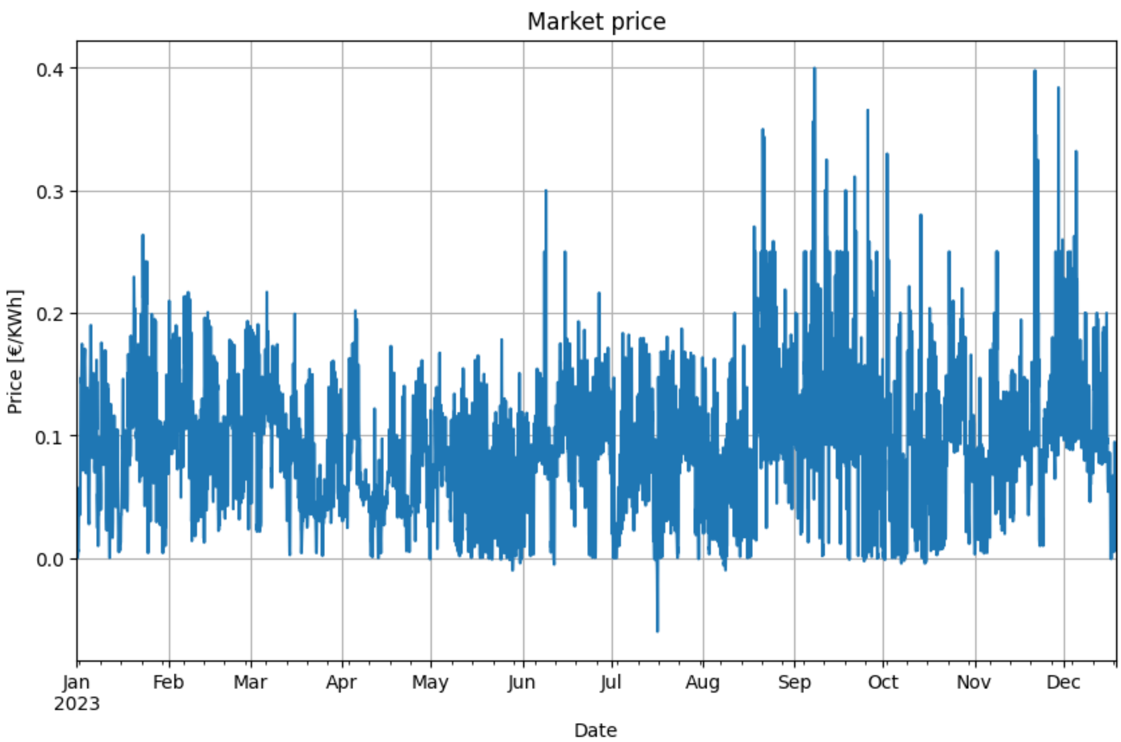

Figure 2 Electricity market price over one year. [9]

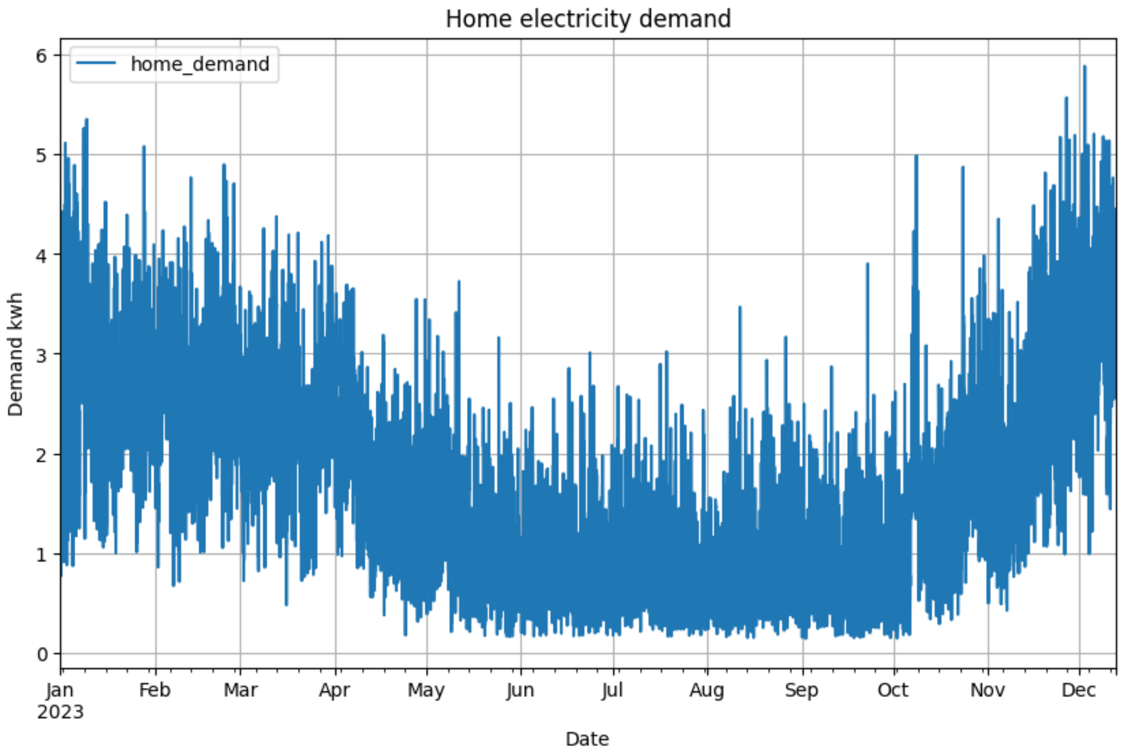

Figure 3 Residential building electricity demand. [9]

2.2 Control algorithm setup

2.2.1 Model predictive control

Model Predictive Control (MPC) is an advanced method of process control that has been widely used in various industries, ranging from chemical processing to aerospace and automotive applications. MPC utilizes a model of the process to predict the future state of the system over a finite time horizon. At each control interval, MPC solves an optimization problem, where the objective is typically to minimize a cost function subject to system dynamics and constraints. This optimization yields an optimal control sequence.

MPC is particularly valuable for its ability to handle multivariable non-linear control systems where the inputs and outputs may be constrained by physical or operational limits. By incorporating constraints directly into the control problem, MPC can ensure that the system operates within safe and efficient parameters.

In the context of energy management systems, the ability to integrate constraints makes MPC an attractive option. It allows for sophisticated control strategies that can dynamically adjust to varying conditions while respecting equipment limitations and operational safety.

This master thesis explores a home energy management system that leverages a Model Predictive Control (MPC) algorithm. The system integrates forecasts to optimally manage the charging and discharging of a battery connected to a photovoltaic (PV) system and the electricity grid. The objective is to minimize electricity costs and maximize the efficiency and lifespan of the battery system by making smart decisions on energy use based on various inputs and constraints.

2.2.2 Cost function tuning

In MPC, the tuning of the cost function plays a crucial role in prioritizing different aspects of the control objectives. By assigning weights to different terms in the cost function, one can emphasize certain performance criteria over others. Since MPC often employs quadratic optimization, the terms of the cost function are typically squared. This squaring is beneficial as it amplifies the importance of minimizing errors, thereby assisting the solver in focusing on reducing overshoots and deviations from set points. For example, higher weights might be assigned to terms associated with energy consumption to prioritize cost savings, while lower weights could be applied to operational speed adjustments, depending on the specific goals of the system being managed. The strategic selection and adjustment of these weights allow the system operator or the algorithm designer to finely tune the system's response to various operational demands and constraints.

2.2.3 Stochastic MPC

Stochastic MPC extends the capabilities of traditional MPC by incorporating model uncertainty and prediction variability into the control process. Unlike deterministic MPC, which assumes that all model predictions and external inputs are exact, stochastic MPC deals with the uncertainty inherent in real-world systems. It does this by developing control actions that are optimized not only for a single predicted future but for a range of possible outcomes. This approach allows for more conservative control commands that aim to ensure reliability and safety under uncertain conditions [10]. For example, stochastic MPC can adjust the charging of a battery system conservatively to avoid potential overcharging due to unexpected surges in solar power production.

However, in this thesis, the application of stochastic MPC was not adopted but was considered during the research phase. The decision against its implementation was based on the relatively stable nature of the inputs being used, historical data on home electricity demand and PV production. Since these data sources provided a reliable basis for predictions without significant deviations, the added complexity of stochastic modelling was deemed unnecessary. Moreover, in the context of this specific household energy management system, preparing for the worst-case scenario through conservative estimates of PV production and demand could be adequately addressed within a deterministic framework. This simplification avoided the computational overhead and complexity associated with stochastic methods while still achieving robust and reliable system performance under the assumed conditions.

2.2.3.1 System Configuration and Control Strategy

This thesis introduces an approach focused on the rate of change in battery discharge, which essentially measures how quickly the battery's energy is being used. This control variable is incorporated into the cost function to generate a smooth control signal. It creates a user experience where it feels like the algorithm has made a deliberate decision to either charge or discharge the battery gradually, rather than abruptly switching between these states at every prediction timestep.

To handle real-world challenges, such as the inability to sell excess electricity back to the grid without having a separate contract with the grid manager, additional control variable known as a PV production scaler was added. This scaler adjusts the PV output downwards when necessary to prevent the scenario where excess energy has nowhere to go (E.g. battery is full and PV production is higher than the home demand), which could otherwise make the optimization problem unsolvable during times of high solar production and thus the optimization problem infeasible.

Another crucial control variable is the power drawn from the grid. Considering that in Europe the grid voltage is typically 230 volts for one phase, we can determine how much power the system should draw from the grid based on the capacity of the circuit breaker using

$$P = \sqrt{3} * PF * I * V$$

where PF is power factor or the efficiency, I is the constant current and V is neutral to line voltage. Using common circuit breaker value of 25 amps for residential house and using PF of 1 for simplicity, the maximum power that can be taken from the grid is 17.25Kw which is also upper bound. In this setup, since selling power back to the grid isn't allowed, we've set the lower limit for this variable to zero, ensuring the system only consumes grid power and doesn't return any.

By strategically managing these variables, the developed MPC helps make the most of both stored and renewable energy, reduces dependence on the grid, and ensures the system operates within its physical limits. This leads to more efficient and reliable energy management in residential settings.

Circuit breaker size [A]	Voltage [V]	Power [Kw]
25	230	17.25

Table 1 Maximum power calculation used in this thesis.

2.3 Cost function setup

2.3.1 System dynamics

Using explicit discrete time-invariant system representation the dynamics can be described as

$$x(t+1) = \boldsymbol{A}x(t) + \boldsymbol{B(t)}u(t) + E(t),$$

$$x = \begin{bmatrix} P_{missing} \\ E_{bat} \\ P_{discharge} \end{bmatrix}, \qquad u = \begin{bmatrix} P_{grid} \\ S_{PV} \\ \Delta P_{discharge} \end{bmatrix}, \qquad E(t) = \begin{bmatrix} P_{demand}(t) \\ 0 \\ 0 \end{bmatrix},$$

$$x(t+1) = \begin{bmatrix} 0 & 0 & -1 \\ 0 & 0 & -1 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} P_{missing} \\ E_{bat} \\ P_{discharge} \end{bmatrix} + \begin{bmatrix} -1 & -P_{pv}(t) & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} P_{grid} \\ S_{PV} \\ \Delta P_{discharge} \end{bmatrix} + \begin{bmatrix} P_{demand}(t) \\ 0 \\ 0 \end{bmatrix}$$

$$= \begin{bmatrix} P_{demand}(t) - P_{discharge} - P_{grid} - P_{pv}(t) * S_{PV} \\ -P_{discharge} \\ \Delta P_{discharge} \end{bmatrix}$$

where:

$P_{missing}$ – Excess/missing power. Should be always 0,

E_{bat} – energy stored in battery – kWh,

$P_{discharge}$ - energy discharged from the battery – kWh,

$\Delta P_{discharge}$ – Rate at which $P_{discharge}$ changes,

P_{grid} – Power demand from grid – kWh,

S_{PV}– PV scaler, used to downscale PV production,

P_{demand} – Electricity demand from the residential building.

2.3.2 Objectives

The overarching goal of the cost function in this Model Predictive Control (MPC) framework is to optimize two main objectives: Economic Efficiency and Battery Longevity. The system's inputs consist of the discharge rate change, the power required from the grid, and the PV production scaler, each adjustable at each timestep throughout the prediction horizon. Given that the input data are in one-hour increments, the control variables are updated hourly. For instance, with a 24-hour prediction horizon, the MPC algorithm will generate 24 distinct control vectors, each corresponding to an hour within that horizon.

2.3.2.1 Economic Efficiency

The power drawn from the grid is calculated in conjunction with the market price, ensuring that energy consumption during periods of lower prices is numerically equivalent to lesser consumption during higher price periods. This segment of the cost function, referred to as the “demanded electricity cost” is further amplified by a weight factor, thereby prioritizing it as the most critical optimization parameter within the cost function. To reduce the overall cost of $C_{elec}(T)$, only $P_{grid}(t)$ can be changed as this is one of the control vector parameters and rest of the parameters are constants provided when the optimization begins. Because the cost function must be quadratic, the product of electricity demand and market price is squared. This means that the cost function value will increase when the market price is negative which in our case is not logically correct as negative price is even better than energy produced by PV that has not cost (if initial investment is not considered), as consuming the energy during the negative prices will lower the overall electricity bill. This is formulated as

$$C_{elec}(T) = \sum_{t=1}^{T} (P_{grid}(t) * M_{price}(t))^2 * W_{price}$$

where:

T - prediction horizon length,

P_{grid} - Power demand from the grid for given hour – kWh,

M_{price} – Positive market prices, negative values are replaced with 0 - €/h,

W_{price} – weight.

2.3.2.1.1 Negative prices

In this thesis the negative price range is not considered as the timespan and respective negative price is very small as can be seen on Figure 2. Instead, when market price is negative, zero price is used. As the PV panel production is expected [11] to rise, the negative prices during the summer months are also expected to rise that could make economical gain much bigger. This could be done by adding additional cost function member that will penalize low consumption from the grid during the negative prices. The author purposes

$$C_{neg\_elec}(T) = \sum_{t=1}^{T} (\frac{W_{neg\_price}}{P_{grid}(t)} * M_{neg\_price}(t))^2$$

where:

T - prediction horizon length,

P_{grid} - Power demand from the grid for given hour – kWh,

M_{neg_price} – negative market prices. Positive values are replaced with 0 - €/h,

W_{neg_price} – weight.

If the weight is 1 then market price will be multiplied by the invers value of power demand form the grid, meaning that the higher demand will decrease the overall cost value. As the $M_{neg\_price} \leq 0$, the cost of $C_{neg\_elec}(T)$ is applied only during the negative price range. W_{neg_price} must be adjusted relative to the W_{price} to achieve wanted behaviour where the power from the grid is used.

2.3.2.2 Battery Longevity

Additionally, the cost function incorporates a penalty for the rate of change in battery discharge. This penalty not only smoothens the control signal directed to the actual battery, promoting a steadier discharge rate, but also contributes to reduced battery cycling within a single day, which is conducive to prolonged battery health. This is achieved by using

$$C_{bat}(T) = \sum_{t=1}^{T} \left(\Delta P_{discharge}(t)\right)^2 * W_{bat}$$

where:

T - prediction horizon length,

$\Delta P_{discharge}$ - rate of change in battery discharge,

W_{bat} – weight.

The effect of C_{bat} can be seen on Figure 4, where the battery is cycled only once and the algorithm has decided to charge the battery during the first half of the day and discharge during the second half. This happens because with the $\Delta P_{discharge}$ in the cost the changing of the discharge is penalized while not changing the discharge rate and leaving it charging is less costly. While this alone does not guarantee that the battery is cycled only once in a day, it happens to behave like this in most of the simulated scenarios. This can be seen on the Figure 4 where the simulation was done over half a month and the battery was cycled 15 times while using only C_{bat}.

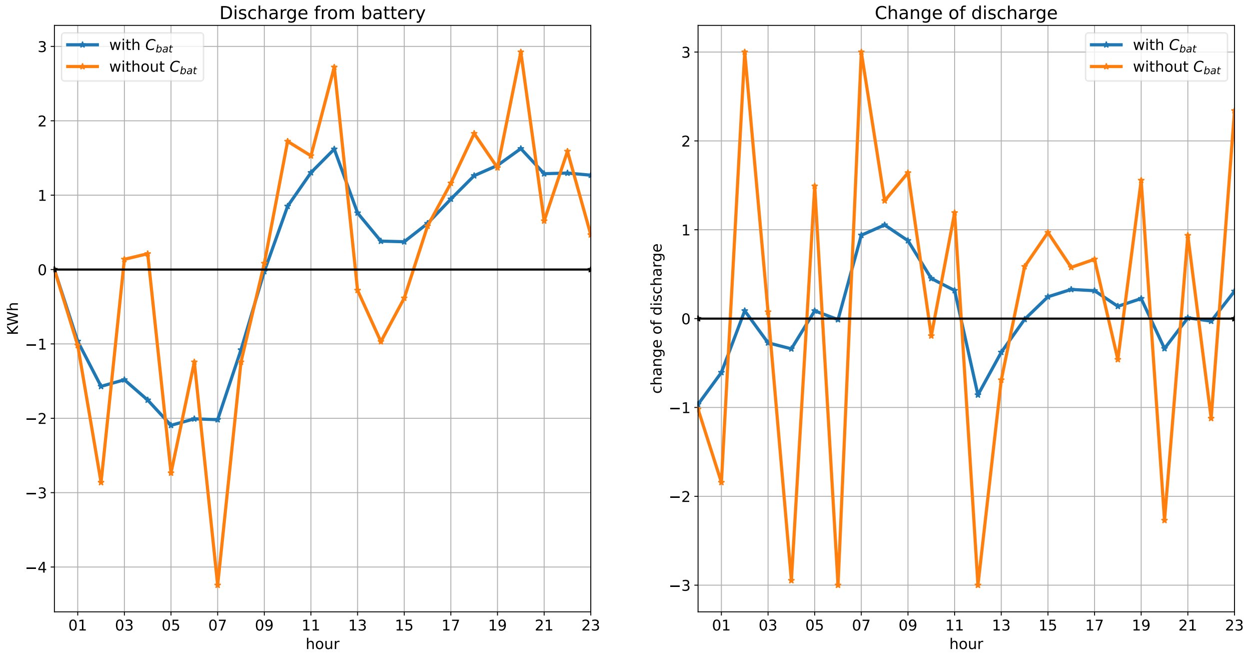

Figure 4 Effect of C_{bat} in the control signal for the battery discharge.

2.3.2.2.1 Usage of discrete elements in cost function

Before using C_{bat} discreet charging cycle counting was used to penalize multiple charging cycles in one day. Charging cycle was defined as battery moving from charging to discharging state

$$C_{bat\_discreet}(T) = C_{cycles}(t) * W_{bat\_discreet}$$

where:

T - prediction horizon length,

C_{cycles} – Number of charging cycles over prediction horizon T,

$W_{bat\_discreet}$ – weight.

This is bad because the cost function becomes discreet which cannot be solved very well using quadratic optimization methods. Most of the simulations ended with IPOPT solver exiting with error code indicating that the optimization problem is infeasible. To mitigate this one solution would be to use approximation of discreet functions as can be seen on Figure 5. While this solution was extensively explored, the author did not implement this method as ΔD_{rate} is much more robust and works in simulations that are longer than one day.

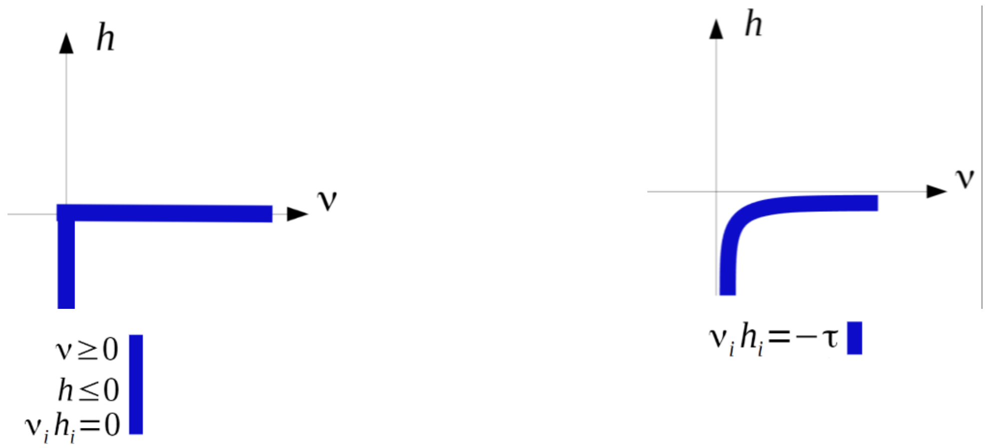

Figure 5 Left showing the discreet version and right showing non-discreet approximation. [24]

2.3.2.3 System constraints

Beyond the control parameters, the cost function is constrained by non-negotiable conditions: the energy content in the battery cannot exceed the capacity of the chosen battery size, enabling simulation compatibility with various battery configurations. Furthermore, the household's electricity demand must always be satisfied. This means that $P_{demand\,\Delta}(t)$ must be always 0. If the battery is charged then the value of $P_{discharge}(t)$ is negative, meaning that its acting as a consumer and to equal out the equation more electricity is demanded by the grid or PV panels.

$$P_{missing}(t) = P_{demand}(t) - P_{grid}(t) - [S_{PV}(t) * P_{pv}(t)] - P_{discharge}(t) = 0$$

$$0 \leq E_{bat} \leq E_{\text{batery capacity}}$$

$$-P_{charge\,max} \leq P_{discharge} \leq P_{discharge\,max}$$

In addition to state space constraints, the control variables are also constrained as described in Section 2.2.1. $\Delta P_{discharge}$ can be left unconstrained because it is directly changing the value of $P_{discharge}$ which is already constrained. Regardless, the bounds for $\Delta P_{discharge}$ could help to speed up the solver because the initial state space is reduced.

$$0 \le S_{PV} \le 1$$

$$0 \le P_{grid} \le P_{grid\,\max power}$$

Formulas above can be rewritten using matrix notation as:

$$\begin{bmatrix} 0 \\ 0 \\ -inf \end{bmatrix} \le \begin{bmatrix} P_{grid} \\ S_{PV} \\ \Delta P_{discharge} \end{bmatrix} \le \begin{bmatrix} grid \max power \\ 1 \\ inf \end{bmatrix} = u_{\min} \le u \le u_{max}$$

2.4 Problem formulation

The final MPC problem with prediction horizon of *T* can be formulated as:

$$\min_{u} \sum_{t=1}^{T} (C_{elec}(t) + C_{bat}(t))$$

$$\text{s.t.} \quad x(t+1) = \boldsymbol{A}x(t) + \boldsymbol{B}(\boldsymbol{t})u(t) + \boldsymbol{E}(t)$$

$$x_0 = x_{inital}$$

$$x_{\min} \le x \le x_{max}$$

$$P_{missing}(t) = 0$$

$$u_{\min} \le u \le u_{max}$$

This problem is nonlinear and solved using CasADi [12] interface and IPOPT [13] solver. The sampling time is 1 hour throughout all the simulations and the prediction horizon is varying based on the simulation length.

2.5 Simulation setup

To use the described MPC, data is needed over the prediction horizon. More precisely home electricity demand and market price are required. To simplify the MPC development no prediction data is used. Instead, historical data from the previous year as a deterministic forecast for the prediction horizon is used. This simplification avoids the incorporation of uncertainty into the simulation, which, while less reflective of potential variability, confers the significant advantage of expeditious feedback from the cost function evaluation.

```
start_date = "2023-06-01"
end_date = "2023-06-02"
current_state = [0,0,0] # [P_missing, E_bat, P_discharge] inital state

testing_data = dataset[start_date:end_date]

prediction_horizon = lenght(testing_data) # 24 in this example

params = {
    "PV_production": testing_data["PV_production"],
    "electricity_demand": testing_data["electricity_demand"],
    "market_price": testing_data["market_price"],
}


set_state_limits()
set_control_limits()
set_inital_state(current_state)
set_cost_function_params(params)

# Tabel with 3 columns (3 control paramters) and
# 24 rows (for each prediction horizon step)
control_vectors = solve()

for control in control_vectors
    state_change = system_dynamics_(current_state, control, params)
    current_state += state_change
    # save current_state for each predicton horizon timestep for plotting
```

The entire prediction horizon is calculated in a single computational instance, and consequently, the nonlinear optimization is executed once, thereby dramatically reducing computational time. This streamlined approach enabled the simulation to compute extended prediction horizons, such as one month, in an impressively brief span of approximately three seconds. The reduction in computational complexity, achieved by forgoing the addition of uncertainty and leveraging historical data, allows for rapid iteration and evaluation of the control strategy, making it particularly suitable for scenarios where speed is prioritized over the precision of stochastic forecasts.

2.5.1 Receding Horizon Control

Receding Horizon Control (RHC), often used synonymously with MPC, is a strategy where the control action is obtained by solving an optimization problem that looks ahead over a finite future horizon, but only the first control action is implemented. After the initial step is taken, the horizon shifts forward, and the process repeats at each timestep. This approach ensures that the MPC continuously adapts to changes in the system's state and the external environment, recalculating optimal controls based on the most recent information. RHC with MPC is particularly beneficial in dynamic systems where future states are uncertain and external disturbances may affect system performance. By continually updating its predictions and optimizations, RHC with MPC provides a robust control strategy that can anticipate and compensate for changes, leading to more stable and efficient system operation.

2.6 Simulation with uncertainty

In the thesis, a practical approach was adopted to simulate the uncertainty inherent in the system's inputs and operational conditions, using a methodology based on Receding Horizon Control (RHC). This approach effectively captures the dynamic and unpredictable nature of real-world systems, particularly in the context of solar energy production and household electricity consumption.

The simulation process began with the initial application of RHC, where a predictive model generated a series of control actions based on the available data. Crucially, only the first control action from this series was implemented—a strategy that is characteristic of RHC. This reflects the real-world scenario where decisions are made with the best available information at the time, but with an understanding that new data may soon alter the situation.

To introduce uncertainty into the simulation, after executing the first control action, random noise was added to the prediction data (input for optimization) that was used during the initial prediction. This noise represented potential errors in prediction or unexpected changes in environmental conditions, such as variations in solar irradiance or sudden changes in electricity demand. Random noise is added to the raw data again on each iteration, so that the previous iteration was done on different noise in prediction data.

Adding noise to the home electricity demand after optimization would defeat the purpose of the system as it can't react to changes that haven't been measured yet because the time between each prediction step is 1 hour (as set by the raw data coming from Elerings [9] database). Real-time changes should be handled by lower-level controller that are described more in Section 1.1.

Following the addition of noise, the system's state was updated with this new, altered data, and the prediction process was repeated. The data window was shifted forward, and a new optimization was carried out using the latest available data, including the recently introduced noise elements. This iterative process was repeated throughout the simulation period, continuously adapting to new information and recalibrated predictions. This method not only tested the robustness of the control strategy against unforeseen changes but also mirrored the process of continuous learning and adaptation that is critical in managing real-world energy systems.

Through this simulation methodology, the thesis effectively demonstrated the system's capability to handle uncertainty and adapt to new conditions dynamically, thereby validating the effectiveness of the control strategy under realistic operating scenarios. This approach also highlighted the strengths of RHC in managing systems with significant variability and unpredictability, providing valuable insights into its application for home energy management systems.

```
start_date = "2023-06-01"
end_date = "2023-06-02"
current_state = [0, 0, 0]  # [P_missing, E_bat, P_discharge] initial state

simulation_data = dataset[start_date:end_date]

sim_length = len(simulation_data) / 2  # 12 in this example
prediction_horizon = len(simulation_data) / 2  # 12 in this example

set_state_limits()
set_control_limits()

output = []

for i in range(sim_length):
    # Take data applicable for this simulation iteration
    testing_data = simulation_data[i:i + prediction_horizon]

    params = {
        "PV_production": testing_data["PV_production"] + pv_noise(i),
        "electricity_demand": testing_data["electricity_demand"] + demand_noise(i),
        "market_price": testing_data["market_price"],
    }

    set_initial_state(current_state)
    set_cost_function_params(params)

    control_vectors = solve()
    control = control_vectors[0, :]  # use only the first row of controls (RHC)

    # save current_state and control command for visualization
    output.append({
        "state": current_state,
        "control": control
    })

    # carry out the controls in simulation
    state_change = system_dynamics_(current_state, control, params)
    current_state += state_change
```

2.7 Technical assumptions

Described systems has multiple simplifications that are not considered in this thesis. One of the most important simplifications that can have significant impact on the results of the simulation is power loss. In real world charging the battery and discharging it later can have huge power losses which is not considered and thus the electricity demand can be higher than simulated in this thesis. [14]

Another simplification is use of power instead of current in all calculations. This might not be achievable with hardware as battery (dis)charging currents depend on the voltage (or the SoC) of the battery, meaning that 3Kw charging power might be not possible with nearly empty or nearly full battery, which should be avoided by default. The significance of this simplification is relatively small because the input data frequency is one hour which means that using current as control parameter would require additional logic that is not relevant for the purposes of this thesis.

Financial gain calculations are comparing home without battery and PV panels and home with developed algorithm that is using PV panels and battery. As the system without battery is not controllable, the comparison must include both components. Simulation where power generated by PV panels is described in Section 3.1.2.

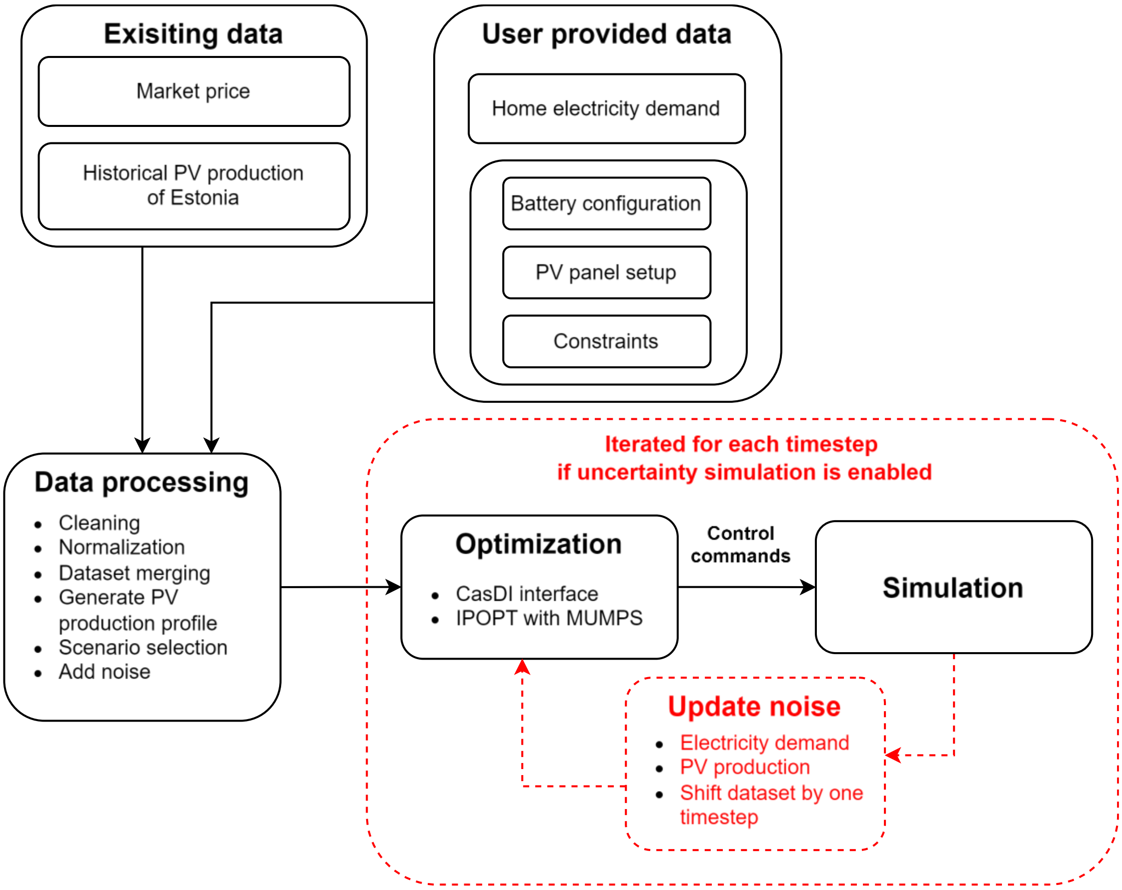

Figure 6 Flowchart of the system. Optimization step involves minimizing the cost function.

3 Data analysis

This section presents the results from various energy management scenarios, analysing the interactions between solar PV production, battery usage, and market price fluctuations. It highlights how the system optimizes energy consumption and costs by intelligently charging and discharging the battery in response to solar output and electricity prices. Extended simulation results demonstrate the potential for significant cost savings, particularly when favourable conditions align. The robustness of the system is also tested under uncertainty, showing its capability to adapt to real-time data variability and maintain efficiency.

All the following simulations were done using the same weights in the cost function which show the robustness of developed control because it can handle all the scenarios without special parameters.

The initial state for every simulation was

$$x_0 = \begin{bmatrix} P_{missing} \\ E_{bat} \\ P_{discharge} \end{bmatrix} = \begin{bmatrix} 0 \\ 2 \\ 0 \end{bmatrix},$$

with constraints:

	E_{bat} [kwh]	P_{grid} [kwh]	S_{PV}	$P_{discharge}$[kwh]
Lower bound	0	0	0	-3
Upper bound	15	10	1	3

Table 2 Constraints used by the simulations.

3.1 Results of different scenarios

3.1.1 High market price scenario

Solar PV Energy Production

Figure 7 illustrates the diurnal pattern of photovoltaic (PV) energy production within a residential setting. It is evident that the PV energy generation predominantly occurs during daylight hours, with a notable peak reaching approximately 2 kWh around noon. This peak corresponds to the highest solar irradiance during the day, which is expected given the nature of solar energy systems.

Battery Charging and Discharging Dynamics

A corresponding graph delineates the charging and discharging cycles of the home's battery storage system. The charge-discharge profile is in direct correlation with the PV production, indicating an intelligently designed control strategy. The battery charges during periods of surplus PV generation—when the energy produced exceeds home demand—and discharges when the PV output is insufficient. This ensures a continuous and efficient utilization of solar energy, reducing the need to draw from the grid.

Market Price Influence on Consumption

Furthermore, the graph reveals strategic consumption behaviour in relation to the varying market prices for electricity. The controller adeptly avoids drawing power during times of high market prices, instead relying on stored energy from the battery. This is particularly noticeable during the late afternoon and early evening when electricity demand typically surges as residents return home, coinciding with an increase in market prices.

Battery State and Optimization

At the zenith of energy storage, the battery holds approximately 9 kWh of energy. This capacity utilization indicates that the battery is not fully charged, which aligns with best practices for battery longevity. Maintaining a daily usage range between 20% and 80% of the total battery capacity is advisable [15], as it keeps the battery voltage around its nominal level, thereby optimizing battery health and lifespan.

Financial gain

In this scenario, if the home user would consume all the electricity form the grid, it would cost 4.3€ without the PV production. Using the developed controller, PV panels and battery, the cost of used electric from the grid would be 0.5€ which is nearly 9 times cost reduction. Author notes that this is handpicked scenario where the financial gains appear to look very big. In other scenarios the difference is not so dramatic.

Electricity cost for residential building with developed algorithm, battery, and PV panels is formulated as

$$P_{grid} * M_{price} + P_{grid} * M_{network\ fee},$$

while setup without battery and PV panels is formulated as

$$P_{demand} * M_{price} + P_{demand} * M_{network\ fee}$$

where $M_{network\ fee} = 0.05$ € , which is little bit cheaper than current today's rate [16], but close enough as cost calculations provide very rough approximation.

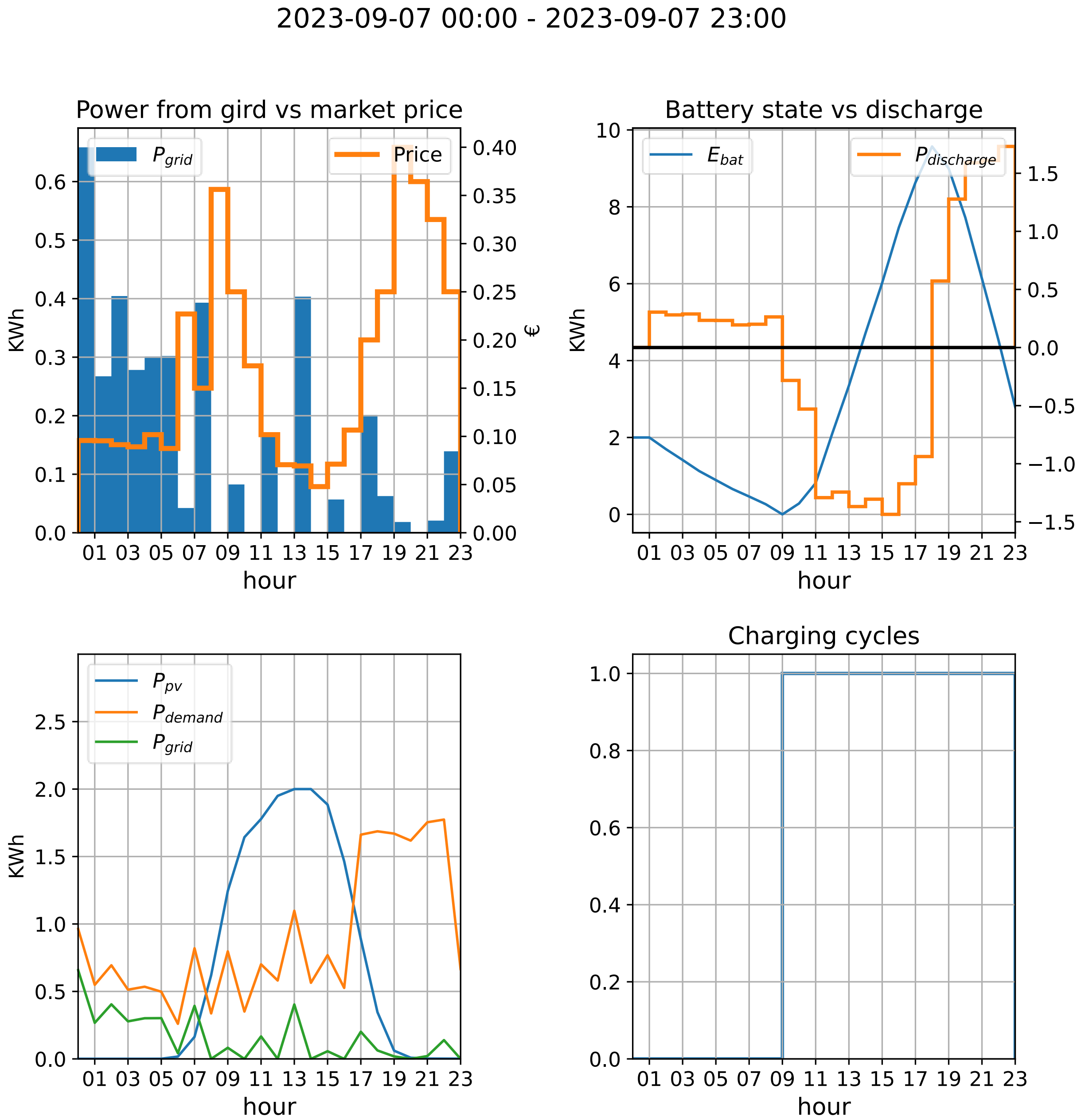

Figure 7 Simulation results of September day where the market price is exceptionally high. The corelation between power demand from grid and market price can be seen on top left graph. Battery charigning start at the peak of the PV panel production and the suddent power demand spike on 13th hour is coverd by grid to not disrupt the battery chraging process unnessecarily.

3.1.2 High electricity demand and small PV production

Figure 8 portrays an energy management scenario in which photovoltaic (PV) panels are producing negligible power, effectively removing them as a significant source of electricity for the period in question. Consequently, the household's energy supply relies solely on the grid and the battery storage system.

During this scenario, set in the early days of January—typically characterized by limited sunlight—the home's electricity demand remains consistently high throughout the day. In response, the implemented controller strategically begins to charge the battery at the start of the simulation, capitalizing on the lower electricity prices available at that time. The battery is charged to its full capacity, accumulating 15 kWh of energy.

As the market price reaches its peak, the controller judiciously reduces electricity intake from the grid and commences discharging the stored energy from the battery. This strategy demonstrates the controller's ability to effectively manage energy costs by leveraging the battery's storage capacity to navigate the fluctuations in market pricing, ensuring a more cost-effective and efficient energy consumption pattern for the household.

Financial gain of this simulation is minimal where's the setup without the battery would cost 5€ and with developed controller and 15kwh battery the electricity bill would be 4.4€

Figure 8 January day where PV production is non-existent, as can be seen on bottom left graph, and at the same time the home electricity demand is very high. The only way to charge the battery is through the grid.

3.1.3 Half-month-long simulation

The same algorithm can be used for longer periods of time by simply changing the prediction horizon. In the Figure 9, the prediction was done for 15 days which is 15*24=360 timesteps. In the upper left graphs, grid power demand and marker price correlation can be seen. When the price drops significantly then the power demand from the grid increases also significantly, reducing the overall electricity cost. Crucially, during the 15-day simulation the battery was also charged only 15 times, indicating that using

$\Delta P_{discharge}$ is working without explicitly modelling the charging cost per day, making the cost function simpler and faster to solve.

Theoretical financial gain shows 80% reduction in electricity cost for this simulation. Figure 9 might look impressive with big cost saving, but in absolute numbers the cost of electricity was reduced from ~50€ to ~10€ which is relatively small and is in best case is enough to offset the cost of buying required devices (PV panels, battery, inverter). Similar simulation during the January, showed that the cost reduction drops from 80% to 20% because there is much less sunlight, and the total PV panel production is smaller. Similar to Section 3.1.2 the primary cost reduction comes from storing the excess PV power that has cost of 0. The longer simulations during summer months show that the big cost savings do not come only from storing the surplus energy, rather the cost savings come from the network fee that is reduced because total consumption from the grid is reduced. In winter months, to make use of the battery the network fee is still unavoidable.

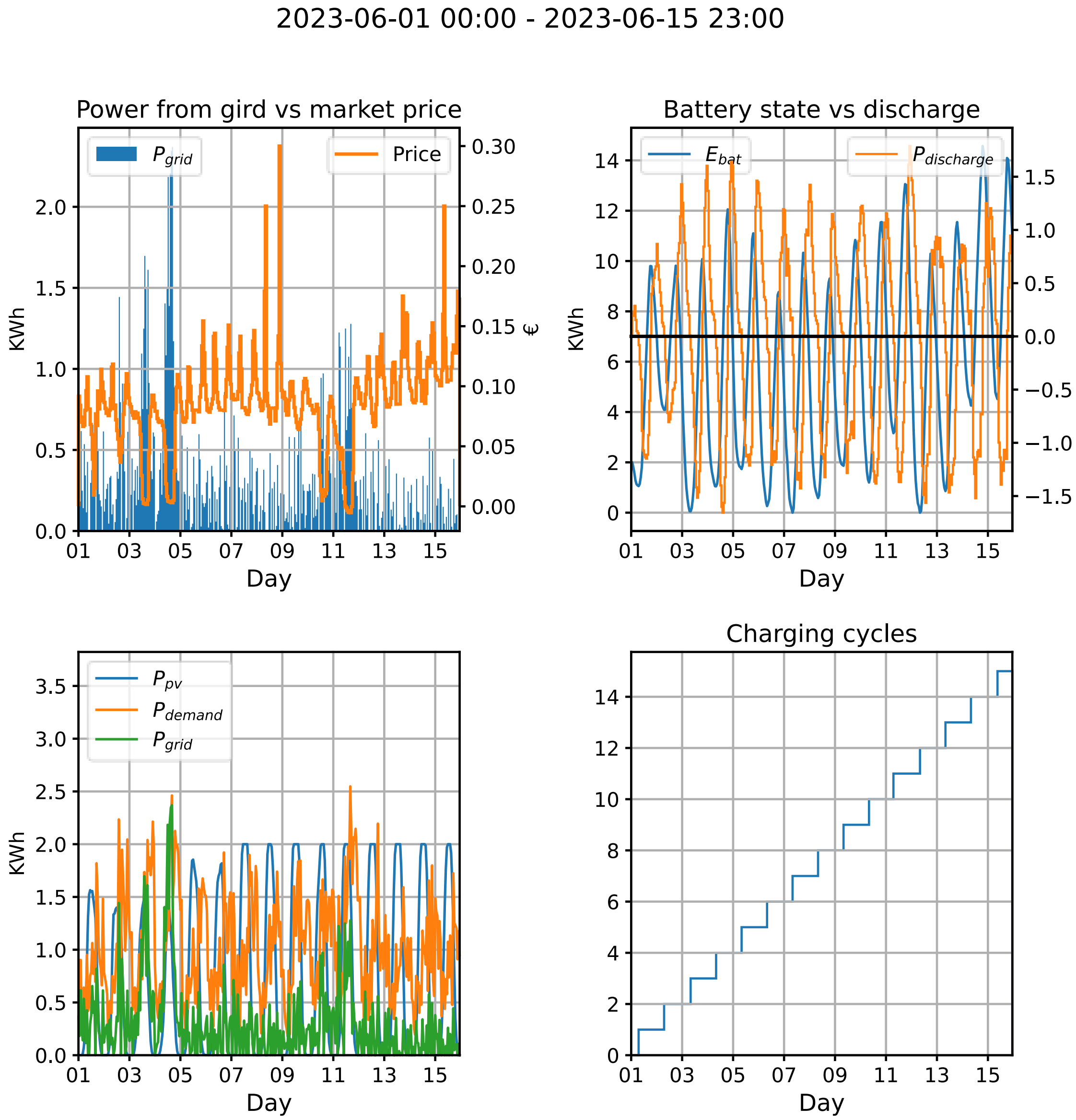

Figure 9 Half month long simulation, showing how the algorithm can be used for longer periods.

3.1.4 Simulation with uncertainty

While using same scenario as in Section 3.1.1 with uncertainty added to the PV panel production and home demand, the simulation looks very similar.

It is very important to reemphasize that the noise is added to the prediction data (that is input for MPC) again for every iteration so that every iteration has different noise applied while still being used for optimization as described in Section 2.6.

As can be seen on Figure 10, the battery is cycled 3 times, showing that $\Delta P_{discharge}$ does not achieve wanted behaviour of one charging per day that is wanted behaviour. At the same time, the charging power is very small and could be disregarded by the lower-level controller. As the power is so small and the home demand behaviour is very radical, where the home electricity demand is very spiky, jumping from hour to hour, the small charging power during 4th and 8th hour is acceptable. Considering that algorithm was able to optimize the peak prices close to zero demand from the grid, the electricity cost was reduced 3 times from 9€to 3€.

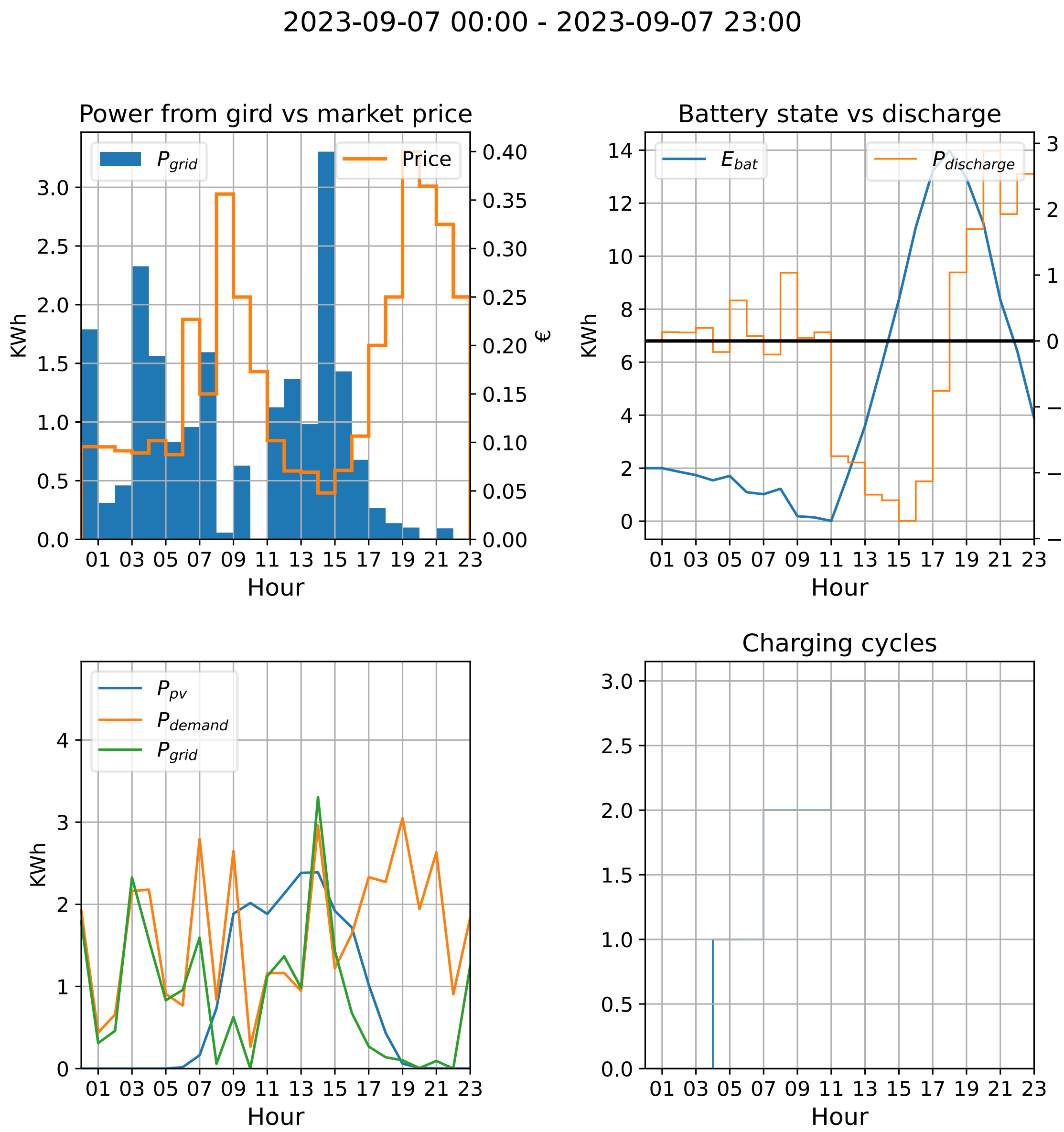

Figure 10 Simulation with uncertainty. Home electiricty demand has become more spiky. The battery is cycled multiple times as can be seen on bottom right graph, but at the same time the power charged to battery is very small which makes it acceptable.

3.1.5 Comparing different simulations

	Total PV production [kWh]	Total demand [kWh]	Total demand from grid [kWh]	Battery [kWh]		Electricity cost [€]		Market price [€]		
				Charged	Discharged	**Old**	**New**	Min	Max	Average
High PV production 2023.06.25 00:00 - 23:00	13.67	26.36	9.71	6.29	8.29	**2.95**	**0.85**	0	0.16	0.06
Low PV production 2023.06.22 00:00 - 23:00	6.17	19.25	10.15	1.78	3.78	**3.13**	**1.49**	0.04	0.16	0.11
High PV production, low demand 2023.06.25 00:00 - 23:00	13.67	26.36	9.71	6.29	8.29	**2.95**	**0.85**	0	0.16	0.06
High PV production, high demand 2023.04.10 00:00 - 23:00	15.43	40.57	21.91	4.8	6.8	**3.29**	**1.88**	0	0.05	0.03
High prices 2023.09.07 00:00 - 23:00	16.08	21.39	3.8	9.57	10.4	**5.4**	**0.64**	0.05	0.4	0.17
Summer 2023.06.01 - 2023.06.30	513.00	691.61	183.8	256	250	**95**	**21**	0	0.3	0.09
Autumn 2023.10.01 - 2023.10.30	152.01	1121	965.51	263	265	**158**	**113**	0	0.33	0.09
Winter 2023.01.01 - 2023.01.30	12	1934	1917	389	391	**295**	**259**	0	0.26	0.1
Spring 2023.01.01 - 2023.01.30	356	1210	850	172	174	**142**	**94**	0	0.2	0.07

Table 3 Comparison table showing the wide variety of simulation and the effect of the control algorithm that can be measured using electricity cost. As can be seen, the effect of the battery and PV production reduces during winter months.

Table 3 shows different simulation scenarios and indicates potential financial gains. The discrepancy between charging and discharging values comes from the initial state. Initially the battery has 2 kWh worth of every stored which means that discharge value can be bigger than charging. Number of charging cycles is not added because it is correlating exactly with the simulation length. Only exception is winter simulation where instead of 15 cycles the battery is doing 21 cycles. Why and the effect of those extra cycles are like in uncertainty simulation and described in Section 3.1.4.

Table 3 indicates that electricity bill is reduces significantly only when there is PV power available that can be stored with battery which allows to use stored surplus energy during peak hours. Using the battery alone has smaller impact on the final electricity bill because even if the market price is small, network fee still applies in addition to the market price, which is constant.

3.2 Validation

The system was not validated with real world simulations and would require additional work to allow for real world testing. Considering the simplification of the setup, validation was done by comparing metrics like electricity bill and comparing energy coming in and out with and without developed algorithm to check if the system is numerically correct.

3.2.1 Comparing results with other work

Similar work had been done towards optimizing control commands for battery using MPC where the goal objective is slightly different. The following [17] work is done also in TalTech and shared the original raw data with author of this thesis so that the comparison between two implementations could be done. The work done [17] is slightly different and more sophisticated by implementing battery degradation to make the economic viability calculations more realistic.

The raw data used for comparison was taken from [17] that is slightly different from the previous simulations done is this paper. PV panel production and home demand data is denser, having sampling frequency of 5 minutes, where previous simulations in this thesis had sampling frequency of 1 hour. The input data was resampled with 1 hour frequency and calculating kWh values for each hour by simply summing the hour values and dividing by 12.

Another significant difference is that in [17] real data recorded in TalTech [18] testing home was used instead of generated and approximate PV production data. This provides more realistic scenario and also indicates that developed algorithm in this thesis can work with actually recoded data as well as simulated data.

Figure 11 and Figure 12 were generated to compare the results of the algorithms. As can be seen on Figure 11, the battery is charging graph has very high peaks in it which means that the battery is charged for short period very rapidly, while on the Figure 12, the battery is charged more smoothly. Both Figures are starting the battery discharge during the evening around 19:00, but on Figure 11 the discharging happens much faster and reaches nearly empty battery at the end of the day.

In this one comparison scenario, both solutions generated very similarly solution, showing that the simplified method can be used to approximate the charging cycles and electricity bill reduction, allowing to generate specific scenarios where homeowner could simulate different PV panel and battery size setups to find the optimal setup for their use case.

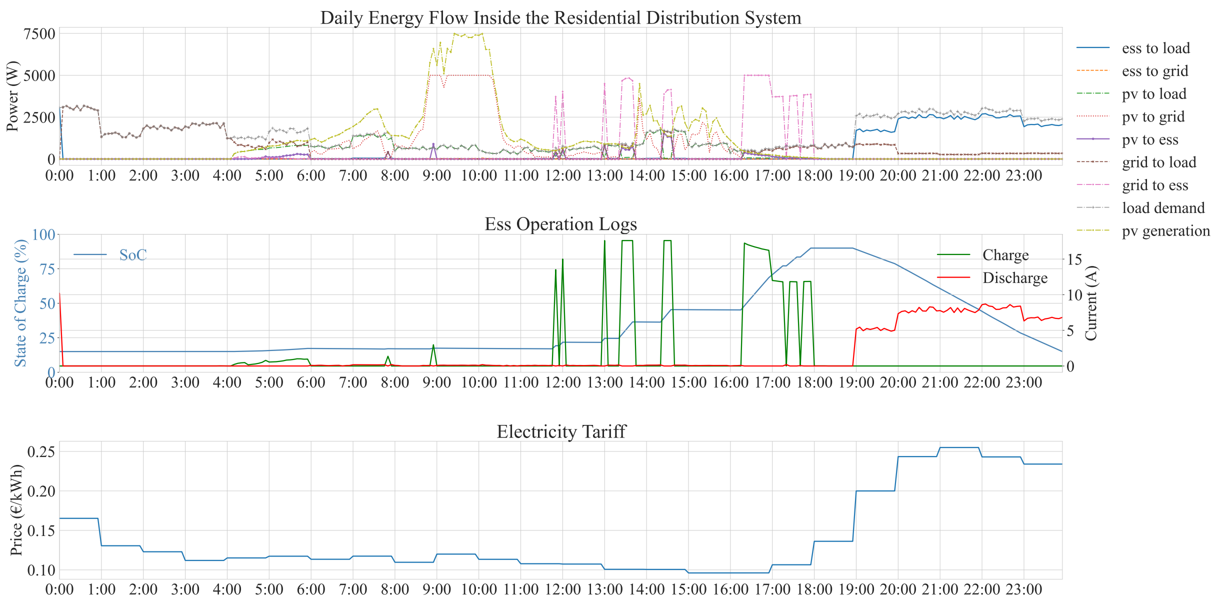

Figure 11 Results of [17]. Ess stands for energy storage system (battery)

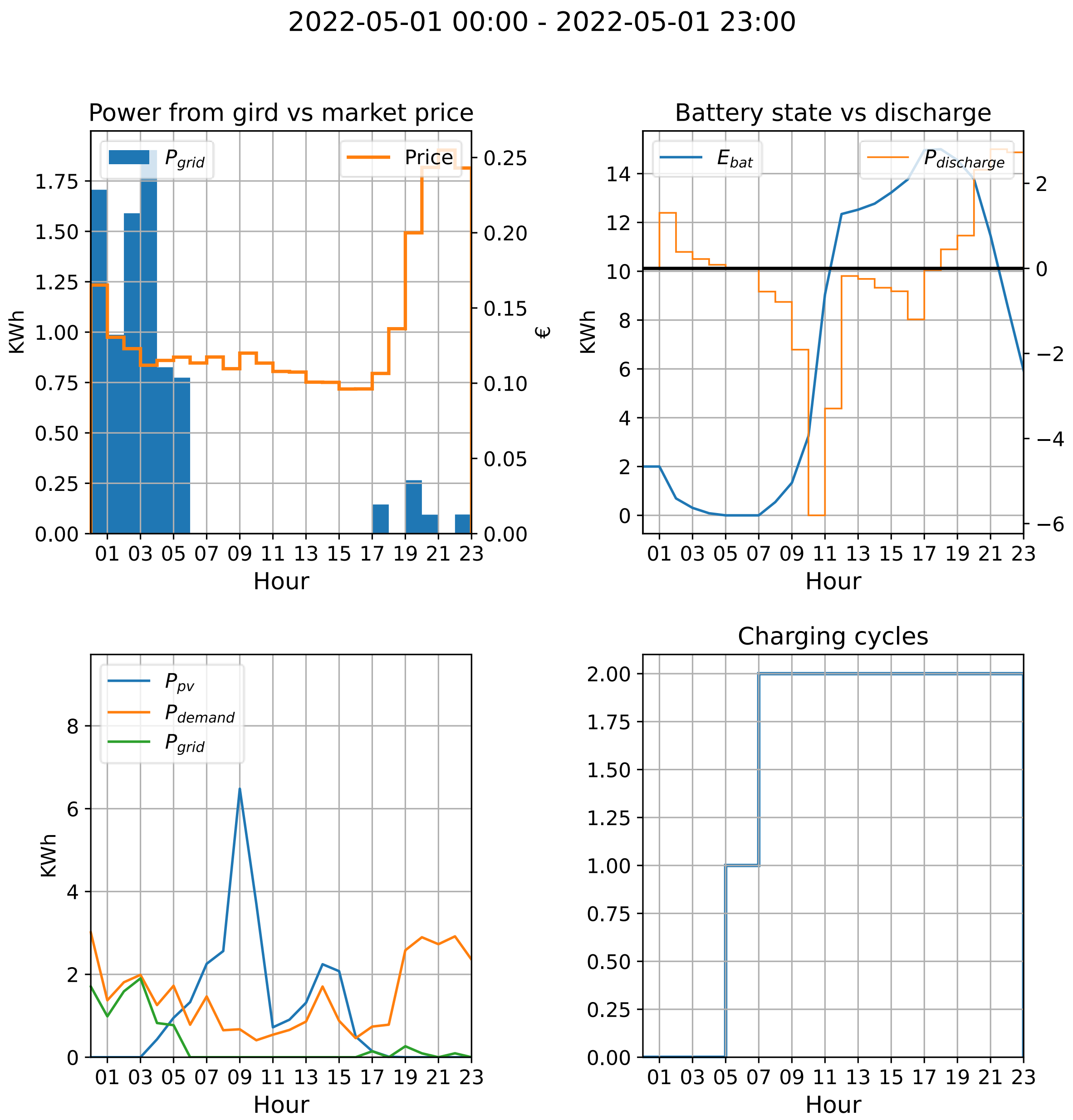

Figure 12 Simulation using algorithm developed in this thesis and using the same raw data as in Figure 11

3.3 Economic feasibility

Calculating the economic feasibility consists of a lot of variables that change for every use case (E.g. electricity demand profile, price of the components etc) and thus the calculations done here are approximations and just to show the potential effects of installing such system in real world.

3.3.1 Required components

Figure 13 describes what is the expected configuration of real hardware setup. Battery can be charged, directly from charge controller or it can be charged through grid using separate charger for it. The high-level control algorithm in this example is algorithm developed in this thesis with limitations described in Section 1.1. While finding commercial product that would accept high level control commands in current form is not possible, but in principle this can be done and is matter of integration and productization. As IoT devices are getting more accessible and popular while demand for smart and fully integrated systems increases, it's only matter of time when there is going to be need for such high-level algorithms.

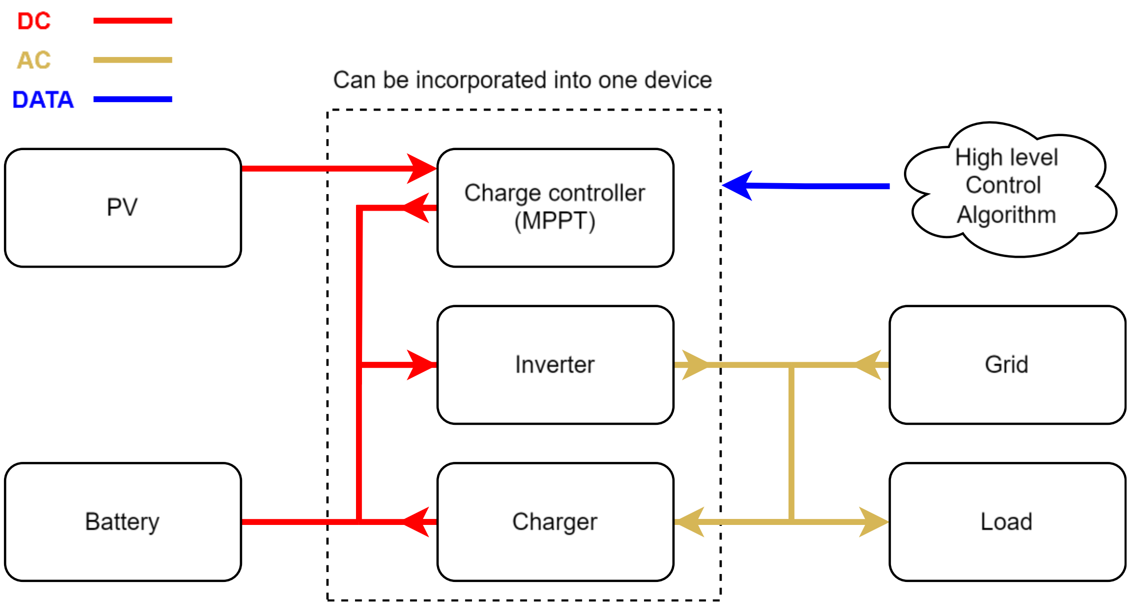

Figure 13 Expected hardware configuration in this thesis.

For simplicity author is combining charge, inverter, and charge controller into one all-in-one solar power solution that are currently available also on the market. This means that regular users only need to worry about PV panels, battery, and all-in-one solar power solution, connection equipment and installation cost.

3.3.1.1 Battery

Most used battery in home is LiFePO4 batteries [15] as they tolerate a lot of charging cycles, are more stables and thus safer while being very heavy which is not a problem in home setting as they are stationary as opposed to cars where energy density is important. LiFePO4 cells has nominal voltage of 3.2V and maximum voltage of 3.6V which means that to get battery pack with maximum voltage of 57V (which is common maximum voltage of inverters) we must connect 16 cells in series. LiFePO4 cells comes in various capacities and to get ~15kWh battery pack as used in this simulation a 280 Ah capacity is chosen as it is widely available. Energy stored in one cell can be calculated with

$$E = V * Q$$

where:

E - Energy stored in a battery [Wh],

V - Voltage of the battery,

Q - Battery capacity [Ah].

The energy stored in one cell is 896 Wh. Using same equation, we can approximate the total energy stored in the battery pack which is 14,3 kWh. This only approximates energy stored because the voltage of the battery changes during the use.

Price for such cells can vary enormously because of the quality and manufactures reputation. For simplicity 100€ per cell is used in the calculations, which gives us 1600€ for the battery pack. As there are additional cost that are related to building battery pack (e.g. BMS and connection equipment) the total cost of battery pack is rounded up to 2000€. Buying a battery pack that is prebuilt with additional communication and safety layers can double the cost, so the end cost varies.

3.3.1.2 PV panels

PV panels come in many different sizes, and power settings depending on the manufacturer and specific panel model. Considering a home with $9 * 9 = 81m^2$ roof area and an average panel size of $2x1{,}5 = 3m^2$ we could fit theoretically $\left\lceil \frac{9}{2} \right\rceil * \left\lceil \frac{9}{1{,}5} \right\rceil = 24$ panels, but considering there are additional limitations (E.g. fastening, chimney etc), 20 panels are used in the following calculation. On average such panels can produce ~400w per panel and the whole array could produce $400 * 20 = 8000w$ worth of power at peak hours. As the panels are not perfect, the cumulative power loss in DC system is around 10%-20% [20] plus additional factors as wrong angle of panels [21], which means that at peak production the array produces $\sim 7200w$. In addition, there is going to be invert power loss discussed later. Considering that such PV panel costs ~150€, the total cost of PV panel array is $150 * 20 = 3000$€. On top of that there is mounting cost that will depend if PV panels are mounted on top of the roof or are part of the actual roof. For simplicity this cost is omitted.

3.3.1.3 Additional costs and summary

As mentioned in Section 3.3.1, all-in-one solar power solution device is used which incorporates all necessary components to use PV panels, charge and discharge the battery and generate AC for home use. On of such system is Victron energy EasySolar-II GX [22], which is selling at ~3600€.

In addition to the components, the installation must be done by professional which varies depending on the complexity of the installation between 300-500€ per kilowatt [23]. Theoretical cost of human labour is 4000€. A buffer of 1000€ is added on top of that to cover the cost of wires, mountings, and additional equipment.

Battery pack (~15 kWh)	2000€
PV panel array (~8 kW)	3000€
Devices	3600€
Installation	5000€
Total	**13600€**

Table 4 Summary of costs

3.3.2 Cost benefit analysis

Table 4 Shows that the total upfront cost of such system is 13600€ which is roughly agreeing with other papers [17]. Considering that the expected life expectancy is minimum of 10 year the system should save $\frac{13600}{10} = 1360$ euros every year to break even. Estimated monetary savings can be calculated using

$$\sum_{i=1}^{i} 3\left[\, M_{before}(i) - M_{new}(i)\right]$$

where

i – index of season of the year (summer, spring, winter, and autumn),

$M_{before}(i)$ – cost of electricity without developed algorithm,

$M_{new}(i)$ – estimated cost of electricity with developed algorithm.

Substituting values from Table 3 we can estimate that in one year the system will save

$$(95 - 21) * 3 \ + \ (158 - 113) * 3 \ + \ (295 - 259) * 3 \ + \ (142 - 92) * 3 = 615$$

euros every year, which is more than 2 times less than needed to break even in 10 years without considering power losses during the optimization. Considering that there are no moving parts that require maintenance and LiFePO4 batteries can be cycled extensively, 20+ years lifetime should be possible and additional unknowns in 20 years in electricity prices in Europe with rising inflation the system might pay off in some cases. In addition, the user has some other benefits like protection from short-term power outages.

4 Discussion

4.1 Are the control commands realistic and usable?

4.1.1 Are the control commands optimal?

As the IPOPT solver is using iterative methods to find the optimal solution, the final solution can depend on how the system is initialization and solver options. For this thesis, default settings of IPOPT were use, which are tuned to optimize tolerance close to 0. The default value for *tol* [19] is 10^{-08} which describes the convergence of the algorithm. All the simulations ended with IPOPT reporting optimal solution and which gives strong proof that the calculated commands are optimal considering the cost function and simplifications in the system.

4.1.2 Hierarchical Control Architecture

In the architecture of the energy management system developed for this thesis, the high-level controller operates on a one-hour timestep, aligning with the economic and operational optimization objectives within the Model Predictive Control (MPC) framework. However, the actual consumption of energy in a residential setting fluctuates at a much higher frequency. To bridge this gap, the output from the high-level MPC controller is employed as a setpoint reference for a secondary, low-level controller. This low-level controller is designed to run at a higher frequency, thereby providing the necessary granularity to react swiftly to abrupt variations in electricity demand or supply.

4.1.3 Synchronization and Adaptability Challenges

One of the inherent limitations of the system arises from the discrepancy between the MPC's hourly control intervals and the real-time dynamics of energy consumption. Should there be significant and unforeseen shifts in demand or generation, the pre-calculated control signals may no longer represent optimal actions, potentially leading to inefficiencies or a temporary misalignment with the system's objectives. The challenge is to ensure that the high-level MPC's decisions remain relevant and adaptable to such instantaneous changes.

4.1.4 Real-Time Optimization Solution

To mitigate this limitation, the thesis proposes leveraging the relatively swift computational speed of the MPC optimization cycle, which operates on the order of ~1 second. This feature uniquely positions the MPC to be hosted on a cloud-based platform, facilitating real-time data acquisition and processing. By harnessing cloud computing capabilities, the system can continuously receive updated information on home energy demand and PV production. More importantly, it is equipped to re-optimize the control actions instantly in response to sudden changes in these input parameters.

The cloud hosted MPC can thus act as a dynamic adjustment mechanism, recalibrating the control strategy as new data becomes available, thereby maintaining the relevancy of its output. This approach effectively transforms the MPC into an adaptive and resilient control system, capable of addressing the temporal mismatch between its optimization frequency and the more volatile patterns of energy usage.

4.2 Future work

While this thesis showed that it’s possible to use widely available data to estimate what’s the impact of adding battery storage system and PV panels to regular residential building there are more home appliances that could be added to optimization and to further improve the cost reduction.

One such appliance is HVAC (heating, ventilation, and air conditioning) that is one of the biggest consumers in residential building. This adds additional complexity of potentially modelling home layout with mathematical formulas and considering user preferences. There are already similar systems developed [6] but incorporating this into one big optimization system could potentially bring bigger gains. This would remove simplistic interface that the work currently has where use only needs to provide home electricity demand profile.

Appliances that only add electricity demand like EV cars could be added while keeping the simple interface and providing user information when to charge the vehicle and how much could EV car reduce monthly cost comparing to regular gasoline fuel car.

4.3 How could developed system improve the grid?

If most of the residential buildings would use similar system as developed in this thesis or as developed in [17] then predicting the electricity demand would become straighter forward because each consumer could send out indications on how much and when they need power and what for. Thus, we could optimize the grid in country so that fossil fuels are not used to charge batteries of residential building and better fit the market price and electricity demand against the predicted production of renewable energy sources. There will still be some uncertainty cause by human behaviour that cannot be predicted with current technology, but the grid and market price could potentially become much more stable which is good for everyone in the region.

Implementing something like this on country scale is currently very hard as it would require coordination of every grid participant and as there is not enough motivation to do so on the political level as system like this would be very experimental. Instead, something similar could be implemented on street scale where ~20 buildings are bundled together with such smart home algorithms that could have e.g. battery storage and some local renewable energy generation nearby to allow for optimization on bigger scale than one building and would be suitable testing ground for smart city technology.

5 Summary

The adoption of residential PV systems paired with battery storage is growing due to technological advancements and declining installation costs. These setups often utilize MPC to efficiently manage energy use, maximizing solar power during peak hours and reducing grid dependency. However, the economic analysis reveals that despite the potential for significant energy cost savings, the high upfront costs of PV panels, batteries, and necessary equipment can make these systems economically challenging.

The initial investment for a typical home setup can range significantly, with a comprehensive system potentially costing upwards of €13,600. While operational savings are realized through reduced energy bills and optimized charging cycles, breaking even on such an investment could take up to 20 years under ideal conditions. This timeframe is based on the current energy prices and does not account for potential decreases in component costs or increases in energy prices over time.

Overall, while residential PV and battery systems offer environmental benefits and contribute to energy independence, the long payback period and substantial initial outlay mean they may not be financially advantageous for all homeowners at this point. As technology progresses and costs potentially decrease, these systems could become more viable economically, but currently, they represent a long-term investment that may not break even within the typical lifespan of the components.

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