Fuzzy-Logic Based Home Energy Management System

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Abstract:

The use of Energy Management System (EMS) in Power Systems is thriving. With an increasing amount of renewables and the move towards smart grids and microgrids, Energy Storage Systems (ESS) are gaining an increased importance. To make optimal use of such ESS within the grid, EMS should predict the best time to charge/discharge in order to maximise profit and help stabilise the grid while ensuring the battery's longevity.
This project focuses on creating a framework for the assessment of any EMS structure. Two types of EMS controllers have been investigated, namely Rule-Based Control (RBC) as used in most of the commercial products and Fuzzy Logic Control (FLC). Two variants of FLC have been designed and tested. The assessment includes battery lifetime impact as well as profitability. The used EMS is scaled down to a Home Energy Management System (HEMS). The idea is that solving uncertainties on the household level is applicable to grid-connected battery systems.
The results show that the soft-controlling FLC partly succeeded. By including the possibility to charge the battery from the grid, the result indicates a substantial 85% improvement in service life while the electricity bill decreased by a negligible 1.5% compared to the standard RBC. Although the lifetime model may not provide realistic absolute values, it reliably indicates relative differences in battery degradation between tested EMS.

Preface

This master thesis, conducted by group WPS4-1050, was supervised by Florin Iov and Daniel-Ioan Stroe. I am grateful to my supervisors for their continuous feedback and guidance throughout this project. The project's primary aim is to create a test environment to assess the effectiveness of a Fuzzy-Logic Energy Management System (EMS), regarding battery degradation and profitability. This thesis is an extension of the previous semester's Project, to be found via this link or in the bibliography [1].

The following software and hardware have been used during the writing of this report:

- Overleaf for text processing.
- MathWorks MATLAB for data processing and calculations.
- MathWorks Simulink for modelling and simulation.
- draw.io for image creation.
- Python for API calls

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Acronyms

BMS Battery Management System
EMS Energy Management System
EOL End of Life
ESS Energy Storage Systems
EV Electric Vehicles
FIS Fuzzy Interference System
FLC Fuzzy Logic Control
GA Genetic Algorithm
HEMS Home Energy Management System
IoT Internet of Things
LCOE Levelized Cost of Energy
LCOS Levelized Cost of Storage
LTM Lifetime Model
MF Membership Functions
MPPT Maximum Power Point Tracker
NPV Net Present Value
PHEV Plug-in Hybrid Electric Vehicles
PSO Particle swarm optimization
PV Photovoltaic
RBC Rule-Based Control
SOE State of Energy
TSO Transmission System Operator
WPS Wind Power Systems

List of Tables

List of Figures

Content

1 Introduction

1.1 Background

The future of power distribution is changing drastically. The green transition is challenging and the need for electric energy is consistently rising. In 2022, the Danish TSO *Energienet* predicted that more electricity will have to be transported due to renewable energies often being placed far away from the consumer. Meanwhile, consumers will also need more energy due to the increase of electric vehicles and electric heating systems[2].

The green transition also brings along a major change in the power grid structure, moving from centralized power plants towards decentralized power production. The placement of renewables in regions with low power consumption due to better production conditions creates the issue of overloading power lines in the distribution grid [2]. To showcase this scenario, Figure 1.1 shows the predicted overload in Denmark's power grid in 2040 if no further reinvestment is done.

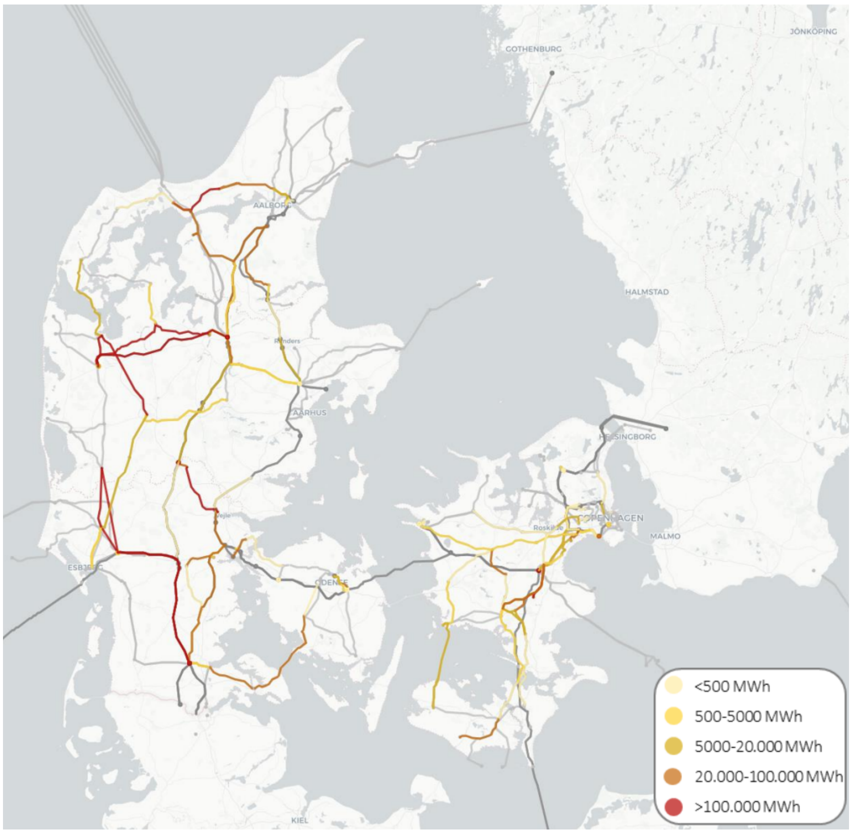


Figure 1.1 Power grid overload in 2040 [2].

To narrow down the problem: The world is facing an increase in electricity consumption, while the green transition urgently requires energy storage capacity that is not yet cheap enough to support renewables fully. To compensate for fluctuations in renewable energies, especially short-term storage, like lithium-ion or pumped hydro, is highly compatible [3]. In order to master this challenge, engineers and researchers are working on various solutions, some of which are shortly described in the following.

1.1.1 Smart homes

The idea of smart homes is that schedulable appliances can be intelligently and automatically shifted by a smart home device to consume power during times of low electricity price, or when the household's own renewable power production is high. These shiftable appliances can, among other things, include heating, washing and EV charging. [4]

1.1.2 Home EMS

Moving from consumers to prosumers, households that not only consume but also produce electricity can help decrease the peak demand.[5] These systems mainly consist of PV panels, a battery system, as depicted in Figure 1.2. They can vary from simple systems that purely ensure the increase of self-consumption and lower electricity bills to complex home energy trading systems [6] that generate profit. This procedure might be less effective than actual Internet of Things (IoT)-controlled devices of a smart home, however, it works with all regular household appliances without the need to buy new smart appliances.

1.1.3 Smart grids

Smart grids are an approach on using scheduling not only on the household level but on a larger scale. This could enhance flexible production, a strong power grid and a better demand response collaboration. This method is called demand response. A major technical challenge is that smart grids require two-way communication. Smart grids highly benefit from smart homes. [7] A major matter in question is the stakeholders and responsibility aspect e.g. policies and regulations, technical aspects, operation and control, as this might be shared among various parties, including utility companies, the government and consumers.

1.2 The Role of EMS in Energy Optimisation

With fluctuating renewable energies and dynamic loads, energy needs to be temporarily stored and released at a later point in time. This is the essence of any Energy Storage Systems. To decide when to charge or discharge, an EMS is needed. It is a broad concept that covers a wide range of applications from large hybrid plants down to the household level. However, the initial concept remains the same. It gathers necessary information to decide whether to charge, discharge or idle an ESS. Depending on the complexity, the included information for the decision-making varies. Input parameters can be temperature, wind speed, solar irradiation, electricity price, estimated consumption etc. Even though residential ESS often include a temperature sensor by the Battery, they are rarely equipped with active heating/cooling systems, even though low temperature can lead to accelerated aging and poor performance. For cooling, passive systems are mostly chosen. Meanwhile, EVs and larger battery plants need to observe this parameter and others that are relevant at all times [8]. A trade off that is to be made is in regards of the complexity of these systems. The more parameters included, the more power and time the processor units need in order to make a decision. Similarly, the higher the update rate, the more power the EMS drains. Additionally, the more complex the Control System, the more expensive it gets. This means that for small systems, often simplicity and low cost are preferred over optimal performance.

1.3 HEMS General Overview

A typical Home Energy Management System is depicted in the following Figure 1.2. The system bears a BESS and a Battery Management System. The BMS makes sure to limit the power output and turn off the Battery in case of under- or over-charge. For renewable power generation, the PV panels and the Maximum Power Point Tracker (MPPT) solar charge controller are responsible. The MPPT can control the output power of the PV in the range from zero to the maximum available power. Centred, an inverter finds its place, connecting the DC side of the PV and battery with the AC side where the loads and the grid are connected. The Power Sensor sends the current Power consumption to the EMS controller. The energy meter measures the power imported from and exported to the grid. The core of the system is the EMS, monitoring the entire system. The EMS takes can take into consideration factor like weather forecast, electricity prices and load predictions.

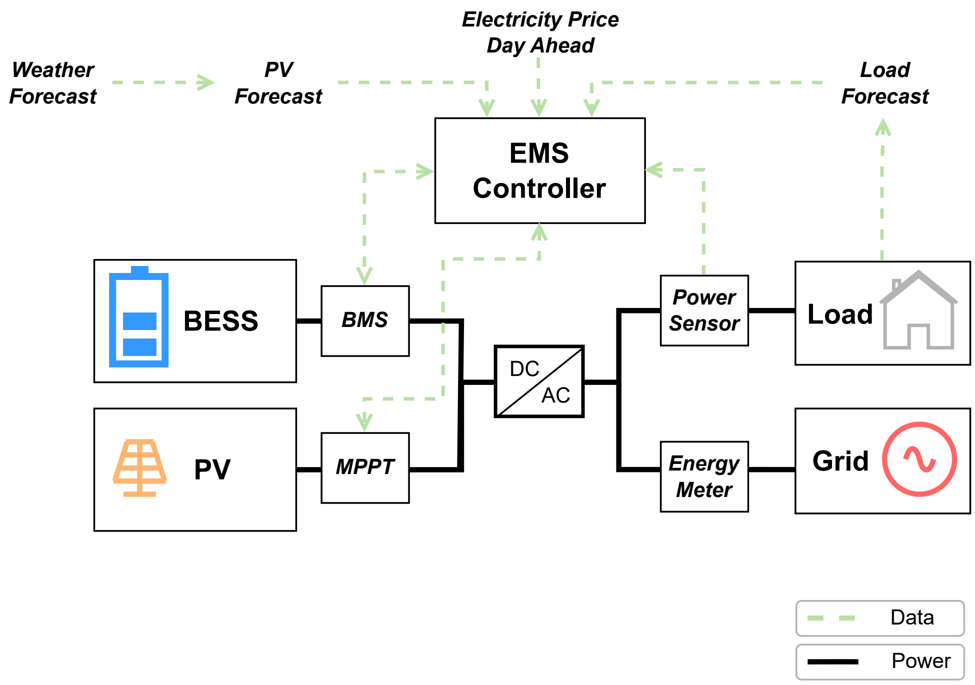


Figure 1.2 General HEMS setup

1.3.1 Applicances

Household appliances can vary. They can be categorized into three categories: shiftable, adjustable, and nonchangeable loads. They are definition is as follows:

- **Shiftable loads**: can be scheduled to start and stop at certain times using IOT and Smart Homes, e.g. washing machine, dishwasher, EV
- **Adjustable loads**: can not only turn on or off but also reduce or increase their load, e.g.

EV, HVAC

- **Non-changeable loads**: can neither be deferred nor adjusted, e.g. kettle, stove, computer, TV, light

This categorization helps understanding the roots of the energy usage in a household. For each category a different approach on optimising the usage is desired. Shiftable loads as well as adjustable nodes require ab directional communication to the HEMS controller. This requires that the devices are able to communicate with the EMS which increases the complexity and cost of such devices due to standardization and the requirement of new purchases. Generally, the integration of such advanced control mechanisms is more justifiable for high-consumption loads. As of today, most of the households do only include non-changeable standard loads. This first version of a fuzzy Logic energy management system controller includes only non-changeable loads. However, the idea is that by creating FIS trees, adjustable loads as well as even shiftable loads can be included in the control.

1.3.2 State of the Art on HEMS

There is a rising number of small and big companies competing in the field, with a large variety of slightly different products with all the same goals: reduce electricity cost, be more sustainable, help balance the grid, make money, etc. However, a short disclaimer is that, while there is a decent amount on the market right now, it is hardly possible to get information about the exact control strategies that are used, as no company wants to share they development openly. Therefore, the assumption that many HEMS do not include smart decision making and instead charge and discharge whenever they can comes from observing personal data gathered by colleagues and friends possessing such systems in their homes. Nonetheless, the different Market products, without diving too much into the depths, are described in the following.

Residential Battery for Non-PV Homeowners

The company 1Komma5° releases residential battery for non-PV homeowners in 2025 [9]. The purpose of the so-called "PowerHarvester" is to let private households benefit from fluctuating electricity prices. The company shows that cheap electricity for homeowners is possible without the need of PV systems. The core of the system is an AI energy manager, which can sell and buy electricity in real-time depending on the energy market value. The customers must pay a small fee for a monthly subscription in order to participate in the trading. According to data, electricity costs can drop up to 50%, which for Consumer with higher Energy Consumption than average (more than 10,000 kWh per year), the System supposedly pays itself of within 6 years. According to the Chief Product Officer, the PowerHarvester not only benefits homeowners, but also helps the ongoing energy transition by adding more storage capacity to the current grid and therefore making better use of the already quite cheap Energy from solar and wind [10].

PV system with battery storage

There are many companies recently offering the combination of PV panels and battery in Denmark, such as Fronius, Growatt, DanSolar etc. Promoting increasingly smafrt Energy Soluions using AI and Machine Learning algorithms.

Growatt states that starting in Q4 2025 and in cooperation with NordCharger[11], it will be possible to participate in grid balancing. Allowing the home battery to support the electricity grid during times of supply-demand imbalance, the homeowner will receive financial compensation. This Auxiliary service will help to improve the stability and sustainability of the grid[12].

Vehicle to X

The idea of Vehicle to Grid (V2G), also referred to as Vehicle to everything (V2X), Vehicle to Load (V2L) and Vehicle to Home (V2H) has been around since some time. The concept is to use the battery of an EV to power your Home (V2L, V2H) or even send power to the grid (V2G) during the day and charge the battery again overnight when the electricity is cheap. The idea so powerful because the average battery of an electric vehicle is already far bigger than usual HEMS batteries. As cars do not normally drive around the clock or consume an entire tank of fuel every day, this concept aims to get the most out of an existing battery. Additionally it is not only a benefit to electric car owners who can gain some cash by not only supplying their households but also sending energy to the grid when the price is high would also benefit to society and help balancing the grid. However this idea does not come without drawbacks. By using EVs in combination with V2G, the degradation of the batteries is accelerated. As of 2025, this technique is still in research. Denmark has announced that Vehicle-to-grid is coming in 2026 [13].

Virtual energy aggregator network

A virtual power plant is a network of decentralised electricity producers distributed along the grid. These producers can consist of households with mounted PV panels as well as a BESS. By monitoring and smartly controlling all these Prosumer households at the same time, a Networks of Virtual Energy Aggregator is created.

The startup *Flexa*, is trying to build Europe's largest of such systems. Partnering up with the German Company *Enpal*[14], one of the biggest renewable energy system integrators in Germany and *Entrix*, an AI innovator in the energy sector, they announced the start in 2024, joining together the first 1000 households. This correspond to a size of around $8MW$ PV power, $5MW$ BESS power and $10MWh$ Energy storage capacity [15].

1.3.3 HEMS and their Impact on the Grid

HEMS, also known as residential EMS can help relieve the stress on the power grid. By generating solar power during the day and charging the battery, load peaks, especially in the afternoon and evening, can be reduced.

A study from Finland showed in a real-life experiment that "HEMS reduced the total consumption of electricity in the winter months by up to 30%, shifted the consumption to off-peak hours and decreased the number of high consumption hours" [16]. In this regard, the here called HEMS where quipped with the capability of shifting electric heating to off-peak hours or simply of being able to reduce the house temperature during peak hours. This could be extended by adding more shiftable appliances and smart controls. Accordingly, the smarter the HEMS, the higher the positive impact on the grid. In the following the impact of EVs and electric heating will be discussed. As a reference for further reading, a single household consumes around 30kWh per day for electric appliances (no electric heating included).

1.3.4 The Role of Electric Vehicles

More and more people are considering buying an Electric Vehicles (EV). As of Jan 2025, only 15.4% of all cars in Denmark are EVs or Plug-in Hybrid Electric Vehicles (PHEV) [17]. Yet, according to [18], "EVs now account for 50.3% of all new car registrations in 2024". Meaning that the total amount is rising steadily every year. This trend can be observed in Figure 1.3.

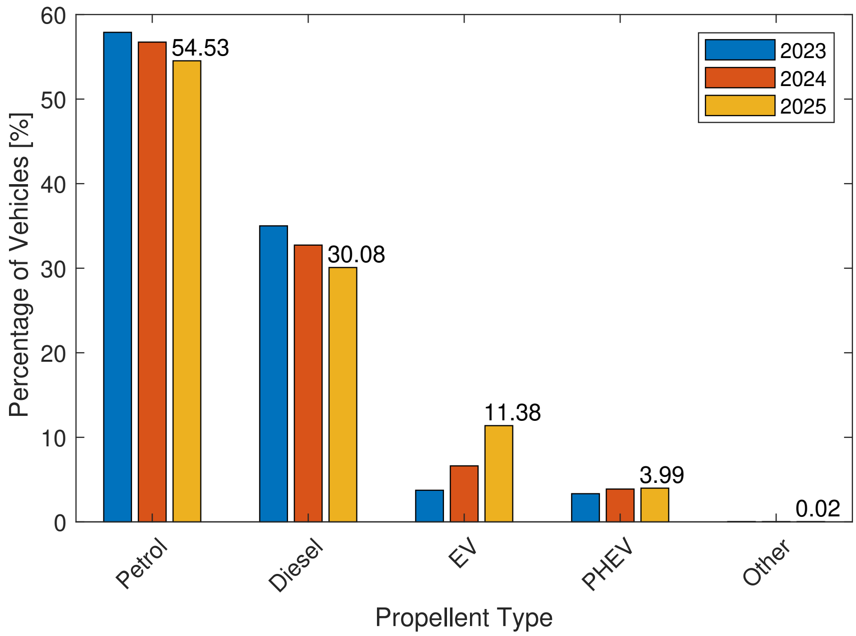


Figure 1.3 Number of vehicles by propellent type in Denmark (data from [17]).

To understand the impact of EVs on regular household consumption, some key values are presented.

An EV with an average range of 450km at today's state of the art has a battery of around 80kWh. The average consumption for EVs in Europe is around 19 kWh per 100 km and can range from 13 to more than 30 kWh/100km [19]. According to [20], EVs in Denmark charge 24.42 kwh/day on average at home.

For comparison, this amount of energy is more than the energy consumption of a regular 4 people household. This means that by including just one EV, the consumption more than doubles. On the bright side, EVs charged at home usually consume during off-peak periods at night [20]. Additionally, most new home charging points allow for programming a scheduled charging cycle.

It's important to take a closer look into the combination of EVs and HEMS that include a stationary Battery:

1.3.5 The Issue of EVs in combination with HEMS

Imagine the situation: The solar panels have been delivering power during the day and charged the batteries such that they are fully charged in the late afternoon. After coming back from a regular work day, the EV is connected to the charger.

Problems :

- With an average HEMS battery ranging from 6 to 12kWh, the recently connected EV will drain the full charge of the battery. Depending on the charging power, the battery will be empty by midnight, which leaves no energy for the household in the morning hours to buffer expensive electricity price peaks.
- The energy finally stored in the EV is expensive, as it causes degradation on both the EVs and the stationary battery. Charging a battery from another battery is never a good idea as it decreases the lifetime of both instead of one, which in the end results in an increase of the final energy cost used to charge the EV.
- Additionally, the overall efficiency is reduced as both batteries have charging/discharging losses. [21]

Solutions:

- EMS should communicate with a smart charger for the EV.
- Automated battery controls could to turn off battery discharging during a certain time in the night, in which the EV is scheduled to charge.
- Exclude the EV charger from the HEMS monitoring. Therefore the EV needs to be connected between the POC and the current sensor of the EMS [21].

Yet, if the only reason is to be carbon neutral, then a person could consider to fully charge the EV from the home battery additionally to the solar, if sufficient energy is provided so it can be avoided to import energy from the grid at all. However, from a cost perspective, as of today in Denmark, where prices fall bottom low during the night, it is not recommendable.

Research is testing further solutions on including EVs as distributed energy storages for households or even the grid and contribute to Demand Response [22]. To sum up, the inclusion of the increasing amount of EVs is complex and brings its problems, but eventually also opens new opportunities.

1.3.6 Inclusion of Electric Heating Systems

Traditionally, heat was provided by burning materials as wood, oil, gas, pallets, etc. In recent decades, methods like solar energy, bio energy, and heat pumps were added. According to [23], "electricity is increasingly used for heating purposes, mainly in the form of heat pumps and electric immersion heaters." The definition is as follows.

Electric Immersion Heaters

In simple terms, the electric immersion heaters provide hot water for your home using electricity.

Current flows through a heating resistance, heating up the surrounding water inside of a tank. This method is simple, yet consumes a decent amount of energy.

Heat Pumps

This technology allows to heat up as well as cool down a an environment using electricity. In this case the electricity is not used to heat up directly, but instead used to transfers heat from a source to the desired destination. By compressing or expanding a refrigerant (fluids or air), the material heats up or cools down, respectively, which then is used as desired. This makes heat pumps quite efficient.

There are different types of HP, while all follow the same principle, refer Figure 1.4.

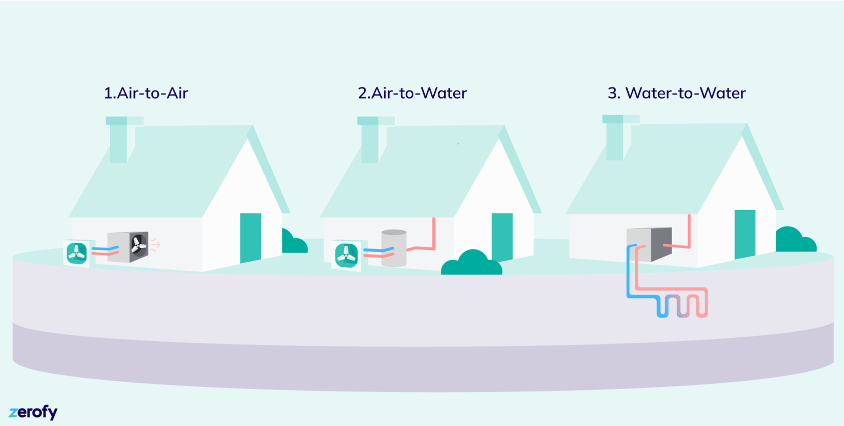


Figure 1.4 Different types of heat pumps [24].

Despite the cold outside temperatures in skandinavian countries, heat pumps are booming [25]. Due to cold outside temperatures Ground source heat pumps outperform air-source heat pumps. However, because of the easy installation and lower investment Cost of Air source heat pumps, both systems are widely spread [26].

As stated above, the main difference between HP and electric immersion heaters is the efficiency. Because HP don't generate but rather transfer heat, they are more energy efficient. A German study shows that HP can generate 3kWh per kWh electricity on average over the whole year [27, 28]. This makes them about 3 times more efficient than electric immersion heaters[29].

So far electric immersion heaters had the advantage of being able to heat water up to a higher temperature than HP. A water temperature of 30°C might be enough to heat the room temperature to 22°C but not enough for a hot shower. That is the reason why HP are mainly used for heating the household. This might change, as the development of heat pumps is making progress, reaching higher temperatures[30].

Heating in Denmark today

As of today, 80% of homes are heated by collective supply, while only 20% are heated individually. In recent years, the Danish government established a scrapping program for oil and gas boilers, supporting the change to climate-friendly heating for houses located outside of district heating areas [23].

Impact on the home consumption
According to a study in Norway [26], 78% of the total electricity consumption of a household is used for heating and cooling a detached house. Besides an EV, it is generally said to be the biggest consumption appliance in a household. Besides better insulation and higher efficiency, researchers are also trying to optimise the scheduling and control. Not only can heat pumps be scheduled to operate on off periods, but also driven at variable speeds, while keeping the temperature range within a comfort zone [31].

To summarise, heat pumps are the future of heating homes, especially in district heating. However, for the applications of detached housing, including a smart control of the Heat Pump into the EMS is definitely a reasonable idea, as these count as the most consuming household Appliance next to EVs.

1.4 Problem Formulation

Generally, any product aims to be profitable. For batteries, there will always be a compromise between gaining profit by maximising usage vs prolonging the lifetime. Most of the algorithms only try to maximise the utilisation, without taking into consideration the stress on the battery. Additionally, the fluctuating power output from solar energy due to changing weather conditions makes it hard to keep the stress on the battery low. Uncertainties within power consumption and PV production increase the difficulty of precise ahead scheduling without overcomplicating the whole decision making process.

The urging question is now, how to optimally utilize BESS in HEMS in order to achieve economic benefits while ensuring life time? This narrows down the key aspects to:

- prolonging the lifetime of the battery while
- reducing the expenses of electricity imported from the grid and
- not over-engineering complex, costly and energy-thirsty, highly cloud-dependent controls for minor profit improvements

1.5 Scope of Project

The Scope of this thesis is to test the control of grid-connected HEMS using RBC and Fuzzy Logic and assess their behaviour. By the end of this research work, the goal is to be able to make a statement on whether Fuzzy Logic has potential as EMS controller or not. The research is backed up with a lifetime analysis and economic metrics to asses the quality of the control. One key factor of this work is the simulation of entire yearly time signals using real weather measurements with a sampling time of 10 seconds and generated load profiles 1-second.

Even if Fuzzy Logic is not the best energy management algorithm compared to more intelligent EMS using machine learning algorithms or nerual networks in addition to load- and PV power forecasting models, this thesis tries to push the limits of Fuzzy logic by testing different approaches and training the fuzzy system based on data.

However, there are some limitations to this project:

- This project does not include smart HEMS. This means no load shifting or dynamic load control strategy is looked into. The focus is only on regular PV + BESS controlled by an EMS controller.
- Electric Heating and EVs are discussed in the introduction but not implemented in the assessed models.
- A power balance approach is considered in the assessment. Consequently, the electrical infrastructure in the house or utility grid is not taken into account
- RBC as standard HEMS in commercial products is used as a baseline to compare the developed control strategies, and might not necessarily be represented in the majority of commercial systems.

1.6 Report Structure

The report structure is as follows:

- **Chapter 1 - Introduction:**
  This Chapter outlines the future problem of overload and high Energy demand that the grid is facing. Diving into reasons such as EVs and Electric Heating Systems, potential solutions are presented. The Scope of this thesis, the HEMS is set, and Limitations are defined.
- **Chapter 1.3 - Overview:**
  In addition to a short System definition, this Chapter presents the State of the Art in commercial- as well as the research field.
- **Chapter 2 - Implementation:**
  After the scope of the project is defined, all modelling parts are described and displayed using flow charts. The Chapter starts with all models required for the test environment and ends with the different EMS controllers tested.
- **Chapter 2.7 - Validation:**
  This Chapter makes that all models work properly. Going through all models, either validation via citation, or via simulations is provided. This assures that models can be traced back to their publication, and newly created models can be trusted on the basis of their simulation-based validation.
- **Chapter 5 - Results:**
  This chapter provides used input data sets for the simulation as well as for each study case undertaken.
- **Chapter 6 - Conclusion:**
  Finally, the summary of the work is conducted, and future work suggestions are stated.

2 System Implementation

This chapter accompanies the process of building the sandbox for the proper testing of the different EMS approaches. The simulation model is split into separate, autonomous models. This enables the opportunity of multiple small models with short run times, reducing time for debugging, testing, and tuning. First, the overall overview is presented, after which the model necessary for the test environment is reviewed. At last, the tested EMS controllers are discussed.

2.1 Framework Overview

To asses the EMS, this is the chosen overall setup:

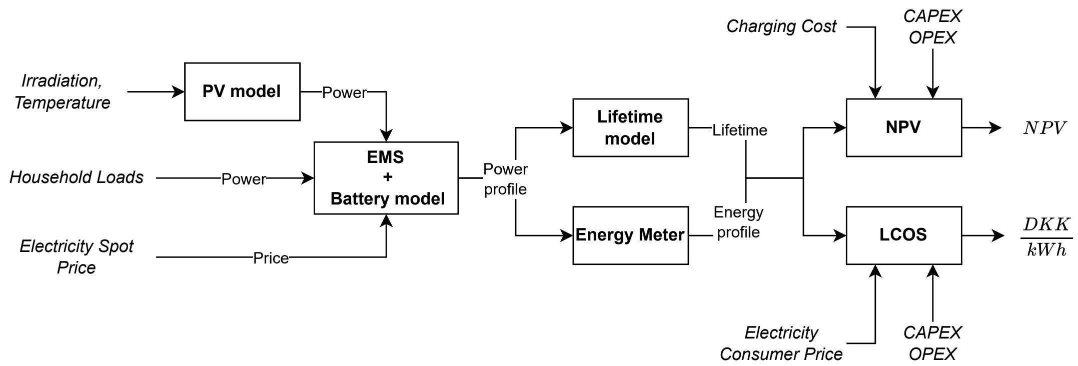


Figure 2.1 System framework.

Each component is explained in detail in the following.

2.2 PV Model

For the PV model, solar irradiance and temperature measurements are taken from [32] with a sampling rate of 10 seconds. These values combined are then used to calculate the corresponding power output of the PV panel. The model allows the relative power output to be easily sized to the chosen panel size. More detailed about the PV model can be found in [33]. Because the power output of the panel P_{rel} is a percentage, this is then scalable to the desired available panel size (kWp).

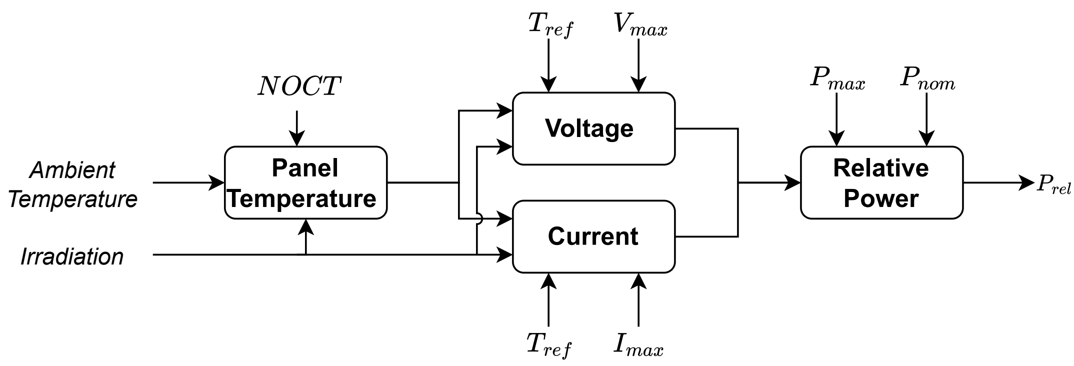


Figure 2.2 Blockdiagram PV Model.

2.3 Battery model

For the battery, a former designed model from the previous project [1] is used. The main principle of this battery model is to verify whether power requested from the EMS can be delivered or not. So it represents the combination of BMS and BESS in one. The incoming power request is firstly checked whether it satisfies the power limitations, and limited if necessary. Then the efficiency coefficient is applied. This means that if the request is to discharge the battery, more power than requested needs to be discharged from the currently held charge, and vice versa. This power is then integrated over its sampling time, and the resulting energy is discarded from the current State of Energy (SOE). Then the check is done to see whether this discharge would push the SOE out of its limitations. This last step decides whether the power request is approved or not.

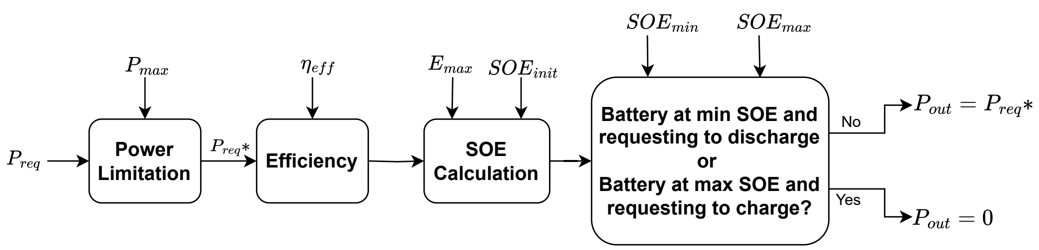


Figure 2.3 Blockdiagram of the battery model.

For all further on simulations a set of parameters values for the battery have been chosen:

Parameter	Value and Unit	
Nominal Power	5	kW
Nominal Energy	5	kWh
Roundtrip Efficiency	90	%
Minimum SOE	20	%
Maximum SOE	100	%

Table 2.1 Battery parameters, based on realistic values [12].

2.4 Lifetime Model (LTM)

The used battery Lifetime Model (LTM) is specifically designed for lithium-ion batteries as described in [34]. It uses a power profile to calculate the resulting capacity and power fade occurring due to cycle- and calendar degradation for each month. The model iterated over each month until reaching the defined End of Life (EOL) at 80% capacity.

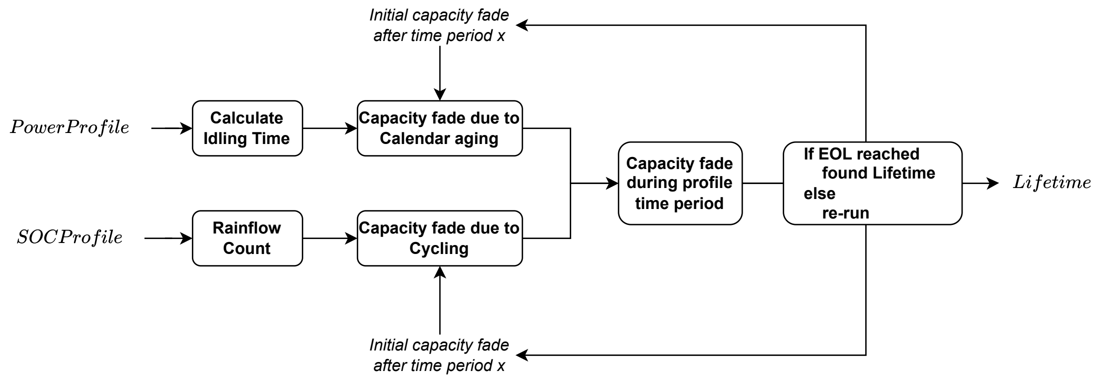


Figure 2.4 Blockdiagram of battery lifetime model.

2.5 Energy Meter

The energy meter is designed as shown in Figure 2.5. By separating the power flow direction, integrating over 15 minute segments and accumulating the final samples to hourly values, the Energy meter is used to measure exported and imported energy from the grid.

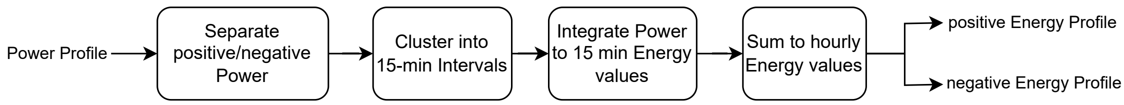


Figure 2.5 Energy meter model flowchart.

The battery power monitoring is measured from the battery towards the inverter. Therefore, all positive values refer to discharged power, and all negative values refer to charged power.

2.6 Cost Estimation Models

There are many financial metrics to asses the value of an asset. In this assessment, the focus is on the amortisation time, computed by the NPV displayed over time and the final LCOS.

2.6.1 Net Present Value (NPV)

The Net Present Value (NPV) is used to evaluate the profitability of an investment. It calculates the difference between the present value of cash inflows (profits) and outflows (costs) over time. These yearly future cash flows are then discounted back to their value today. A positive NPV means the investment is expected to generate profit, while a negative NPV suggests a loss.

$$\mathrm{NPV} = -InvestmentCost + \sum_{n}^{N} \frac{CashFlows_n}{(1+r)^n} \tag{2.1}$$

where

$$CashFlows = Revenue - Expenses - Taxes \tag{2.2}$$

for each year.

Calculating the NPV for a range of lifetimes will result in a curve that shows the turning point ($NPV = 0$) at which an Investment starts to be profitable.

2.6.2 Levelized Cost of Storage (LCOS)

The LCOS model stands for "Levelized Cost of Storage". Similar to Levelized Cost of Energy (LCOE), used for Power production, the LCOS calculates the final cost of Energy, that is discharged from the battery. This cost per kWh value can then be used to compare how financially efficient the Battery is used. Additionally, this metric makes it possible to compare the cost of discharged Energy from the battery not only to other battery technologies, but also to the cost of energy imported/exported from/to the grid, as well as to the LCOE of PV panels, wind turbines and other power generation technologies. This means that the metric is very versatile and applicable. The LCOS formula is derived from the NPV, provided in the Appendix A.1 - A.6

The original formula has been taken from [35] and was created as a generalised formula to compare different ESS. For this thesis, the formula is adapted to fit the specific requirements of lithium-ion batteries. The result is presented below, in Equation 2.3.

$$LCOS\left[\frac{\$}{MWh}\right] = \frac{Investment\ cost + \sum_n^N \frac{O\&M\ cost}{(1+r)^n} + \sum_n^N \frac{Charging\ cost}{(1+r)^n} + \frac{End\text{-}of\text{-}life\ cost}{(1+r)^{N+1}}}{\sum_n^N \frac{Elec_{Discharged}}{(1+r)^n}} \tag{2.3}$$

The LCOS value is calculated by adding up all costs occurring over the lifetime of the battery and dividing it by the discharged energy. All cost values are discounted each year, to resemble the precise value of each cost accounting the yearly discount rate of money. The final LCOS is strongly dependent on the lifetime (operation time) of the battery.

The financial and technical parameters for the LCOS model are chosen as listed in Table 2.2, based on realistic values.

Parameter	Value and Unit	
Investment Cost energy capacity	300	USD/kWh
Investment Cost power capacity	250	USD/kW
Construction Time	1	years
Discount rate r	8	%
O&M cost Energy specific	0.4	USD/kWh
O&M cost Power specific	5	USD/kW
Nominal Power	5	kW
Nominal Energy	5	kWh
EOL	20	% capacity fade
Lifetime[1]	N	years

Table 2.2 Parameters LCOS model.

2.7 Model Verification

In this chapter, the verification of each model is gone through. Depending on whether the models have already been validated and published or were developed as part of this work, the verification process is carried out accordingly.

2.7.1 PV Model

The PV Model was validated and published in [33]. Further verifications are not needed. However, a short visualisation is placed in the Appendix A.2

2.7.2 Battery Model

This model has been carried on from the previous semester's project [1], in which the model has already been properly validated.

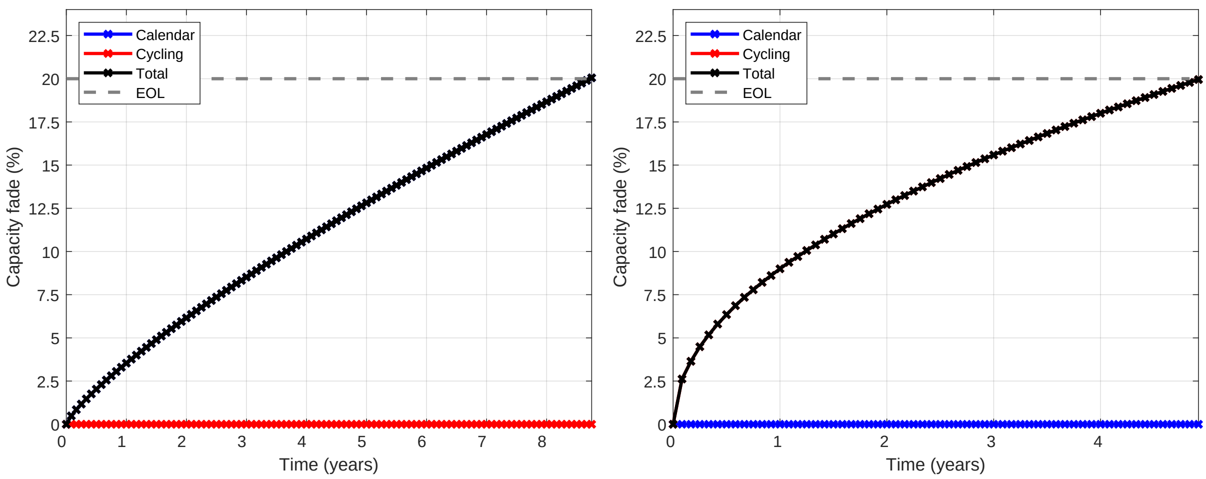
2.7.3 Lifetime Model

The battery lifetime model was published in [34], where the full model is validated using a real test setup. For this thesis, the model was adapted and modified to fit the test environment. However, as no core functions were changed, no new validation is made. A small sensitivity analysis is conducted and results are presented in Table 2.3.

Test Profile	Cycles/year	Lifetime (years)
Idling at 95% SOE	0	8.8
Idling at 50% SOE	0	13.2
Idling at 20% SOE	0	17.5
Full Cycling at 1C	4393	0.9
Full Cycling at 0.2C	879	4.9

Table 2.3 Sensitivity analysis for lifetime model.

These values match well with other sources found as [36]. The expected nonlinearty of the degradation can be observed in



(a) Capacity fade until EOL for idling at 95% SOE.

(b) Capacity fade until EOL for full cycling at a rate of 0.2C.

Figure 2.6 Sensitivity analysis of LTM (Note: the black line is covering the corresponding trace).

2.7.4 Energy Meter Model

The validation of the energy meter is carried out in Figure 2.7. A power test profile is applied to the meter to show proper functionality with different test cases. In the first hour, the power profile jumps to one kilowatt after half an hour. This results in half a kilowatt hour of energy, as expected. Following hours, the constant power of 1kW is metered, and a constant energy of 1kWh is metered. The same test is made with negative power, which means that the direction of the power flow is changed. This can be in the form of charging/discharging a battery or exporting/importing power from the grid. The last two tests, between hours five and six and seven and eight, are to show that more complex waveforms are also metered correctly.

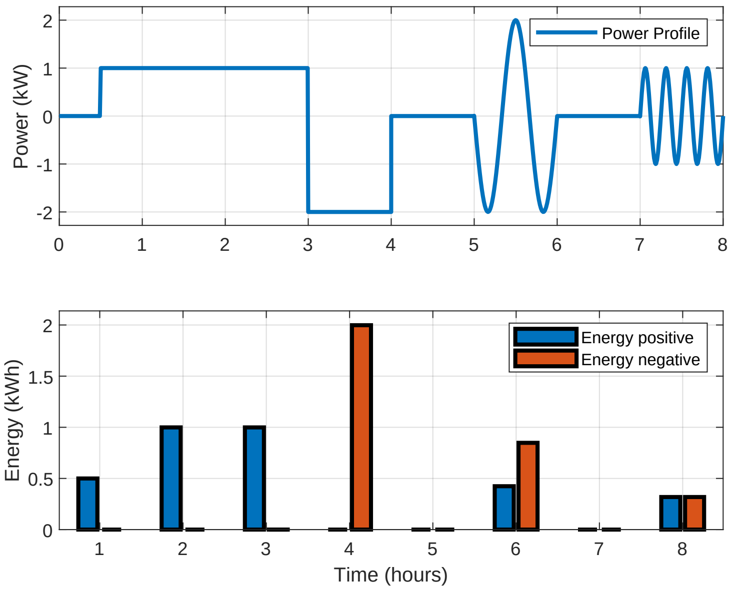


Figure 2.7 Validation energy meter.

2.7.5 LCOS Model

The graph in Figrue 2.8 shows the LCOS using test values from [35] for a varying Lifetime.

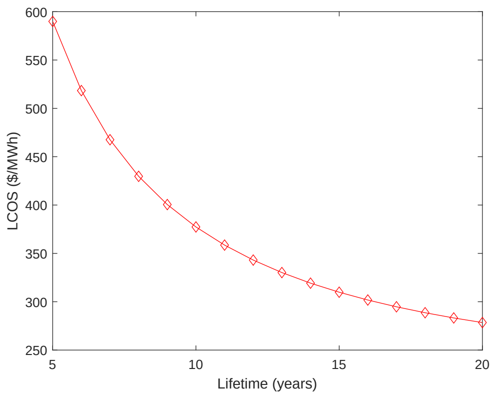


Figure 2.8 Validation LCOS based on different lifetimes.

For a realistic lifetime between 10 and 15 years, the Graph shows an LCOS of between 300 to 400 USD/MWh, which seems realistic when compared to other sources [35, 37]

2.8 Summary

Chapter 2 presents the system implementation and the validation of its individual components. The section begins with an overview of the framework design, processing all separate sub-models of the system.

All important parts for the test environment are then described and explained: PV model, battery model, lifetime model, energy meter and cost estimation models

Finally a verification section of each model follows.

3 Test Scenarios

In this chapter, the input data i.e. electricity prices, etc, for different scenarios is shown. The focus is on the development over the most recent years in Denmark. The data is covering a four years period, i.e. from 2021 to 2024.

3.1 Electricity Price

The electricity spot price in Denmark over the considered period is shown in Figure 3.1. The yearly average fluctuates around 0.6 DKK/kWh. However, a noticeable price peak occurred in 2022 with about 1.6 DKK/kWh on average. This is an increase of 200% to the average of the other years. The reason for this spike was the start of the war in Ukraine. This shows that high fluctuations are possible and should be included in test scenarios.

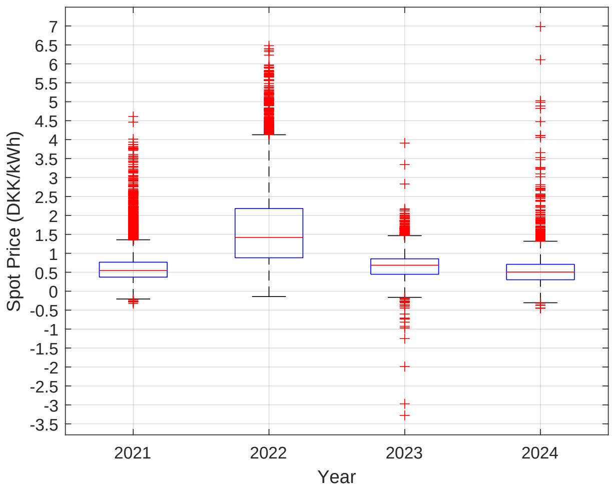


Figure 3.1 Denmark's electricity spot price in DKK/kWh over the last years, presented in form of box plots.

Year	Average price $[DKK/kWh]$
2021	0.66
2022	1.63
2023	0.65
2024	0.51

Table 3.1 Spot price average per year.

An analysis on a daily basis during 2024 shows a clear pattern. The electricity price follows a clear pattern of peaking twice a day, once in the morning between 7 and 8 AM and in the evening between 5 pm and 9 pm. Note that the afternoon peak is not only higher but also stretches over a longer time. Because solar power is produced in the middle of the day, it mismatches the electricity peak. This is why Batteries are so important in combination with PV.

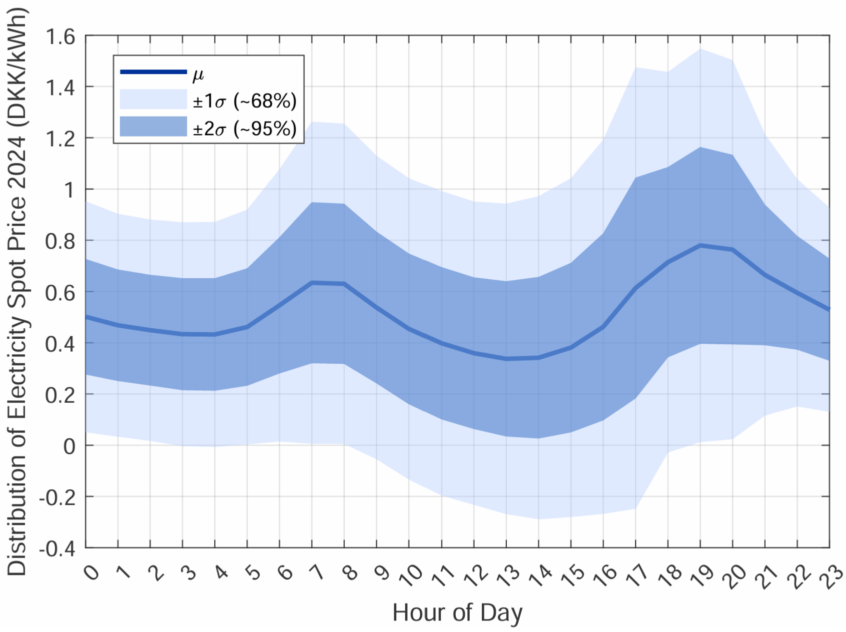


Figure 3.2 Hourly averaged spot price in 2024 [1].

The controller uses the spot price to make a decision for the battery action. However, for Cost calculations of the electricity bill, the consumer price is used. The Price is a composition of multiple factors, which is calculated using following formula:

$$\text{Consumer\_price} = (\text{Spot\_price} + \text{Transport\_costs} + \text{Addendum} + \text{Electricity\_tax}) \cdot (1 + \text{VAT\_tax}) \tag{3.1}$$

More details are available in [38].

A visualisation of the composition of consumer price can be seen in Figure 3.3. The resulting time signal of 2024 can be observed in Figure 3.4.

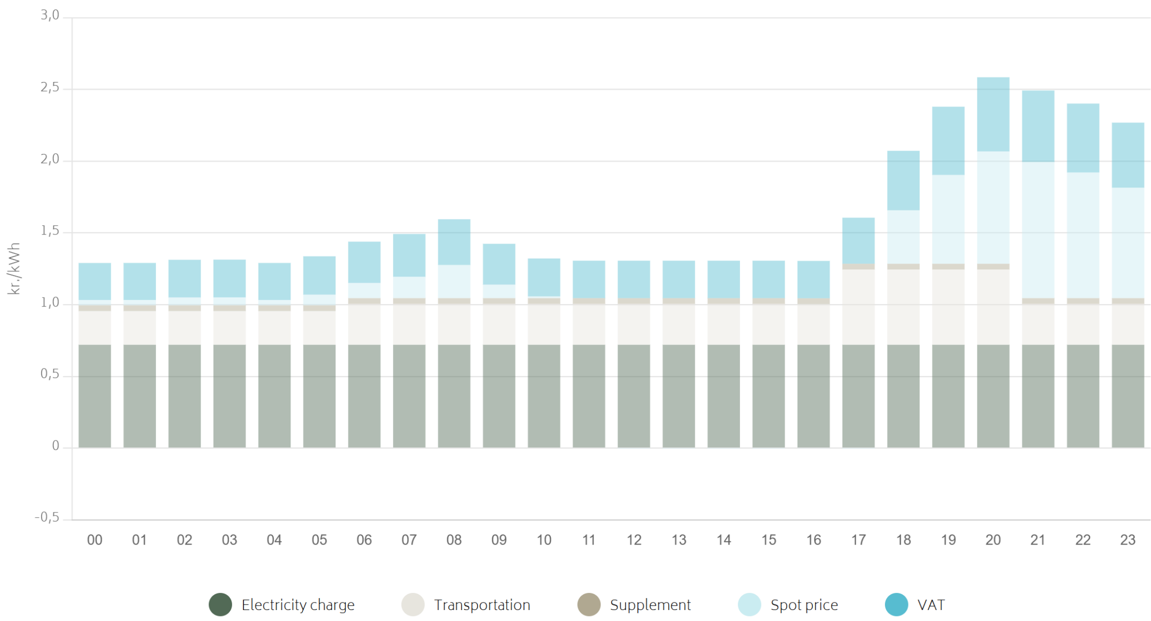


Figure 3.3 Hourly consumer price composition of a local provider in DKK/kWh [38].

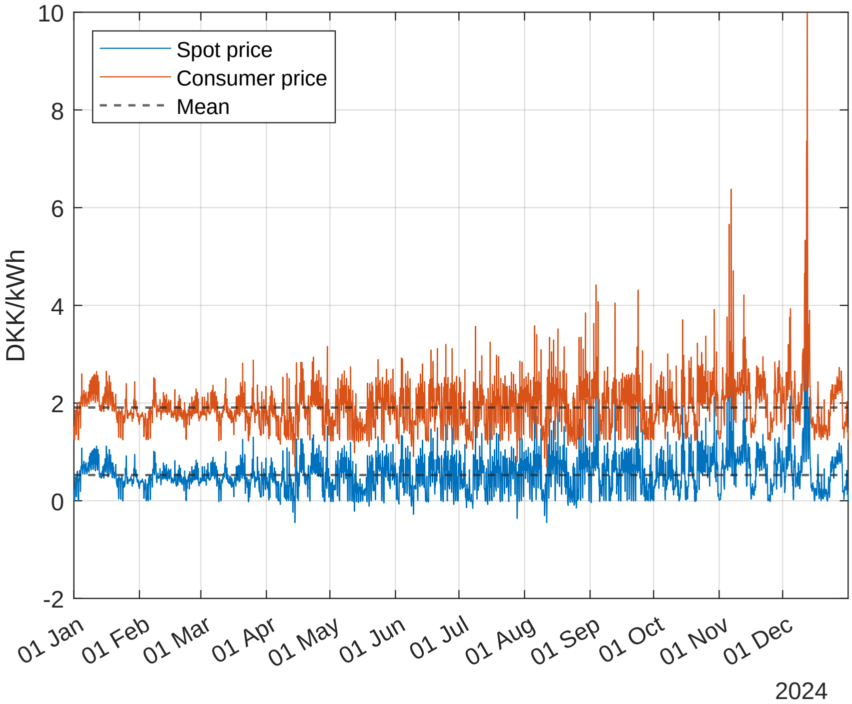
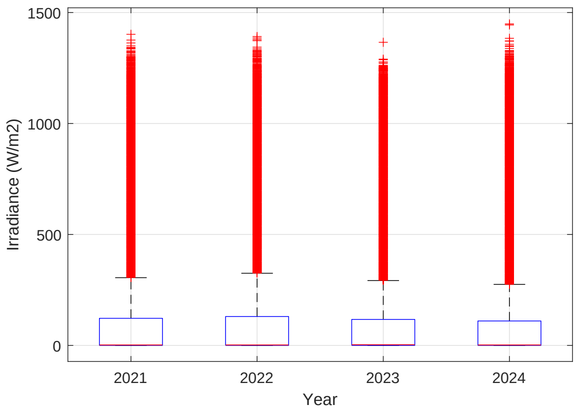


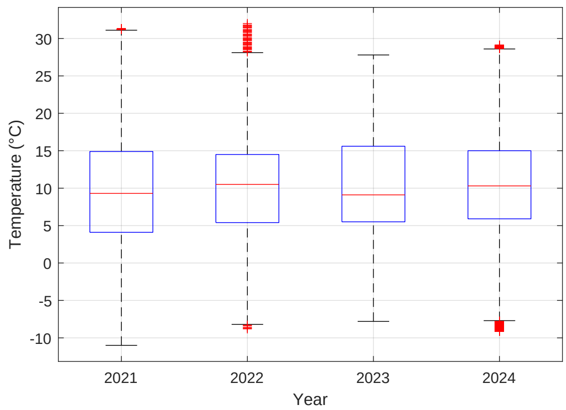
Figure 3.4 Consumer vs spot price in DKK/kWh for 2024.

3.2 Weather

The solar irradiance and temperature data is gathered from a weather station at AAU Esbjerg [32]. The dataset has a resolution of 10 seconds. It appears that temperature, as well as irradiation, do not show major differences between the years.



(a) Irradiation



(b) Temperature

However, computing the produced PV power, a general fluctuation of +-10% is noticeable, as Figure 3.6 indicates.

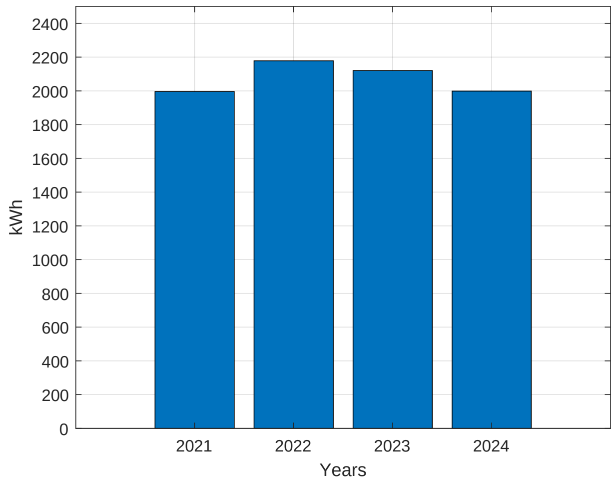


Figure 3.6 Yearly PV production for a 3 kWp solar panel system for the recent years 2021-2024.

3.3 Electricity Consumption

Due to the fact that it was not possible to get load measurements for the entire year with the desired sampling time of at least 10 seconds, the load profile was composed of load generated for three days for summer and winter, with a sampling time of 1 seconds. These three-day blocks were then used to fill up each time of the year. The winter profile ranges from October to March, while the summer profile covers April to September.

The Energy consumption of these load profiles varies between 4.6 kWh and 7.6 kWh per day. These are only synthetically generated test profiles. Based on the available info in the public domain, the synthetic consumption profiles are realistic and can be used in the analysis It can therefore be expected that by using real measurements from a household, the results will not be significantly changed. The consumption of households can vary extremely from household to household. According to an analysis from 2017, the daily average can vary from 2.8kWh up to 14kWh for households without EV or electric heating [39], only depending on the number of inhabitants and their age. Factors like home office, EVs, Electric Heating, etc impact the load pattern even stronger.

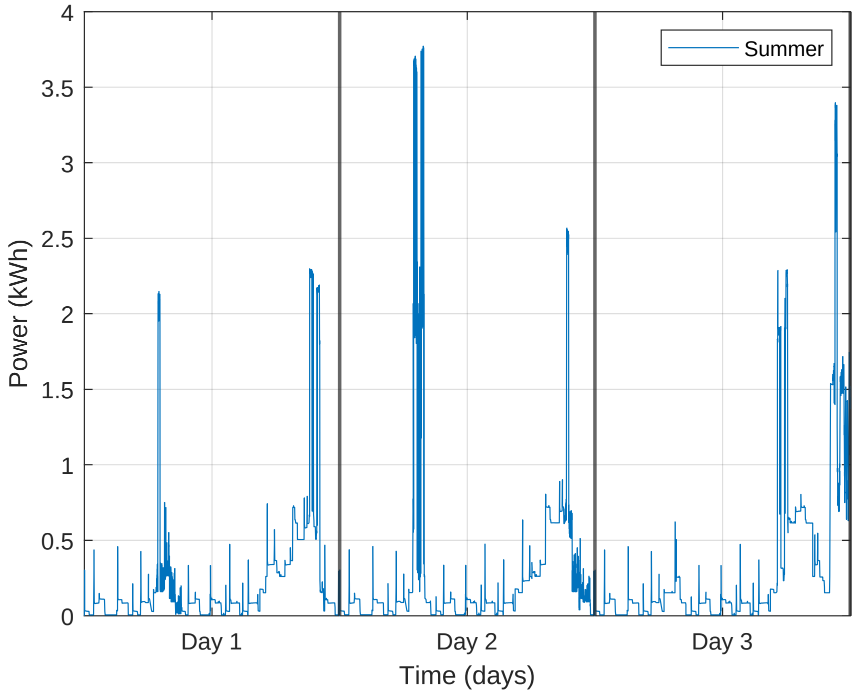


Figure 3.7 Load profile used for all days from April to September inclusive.

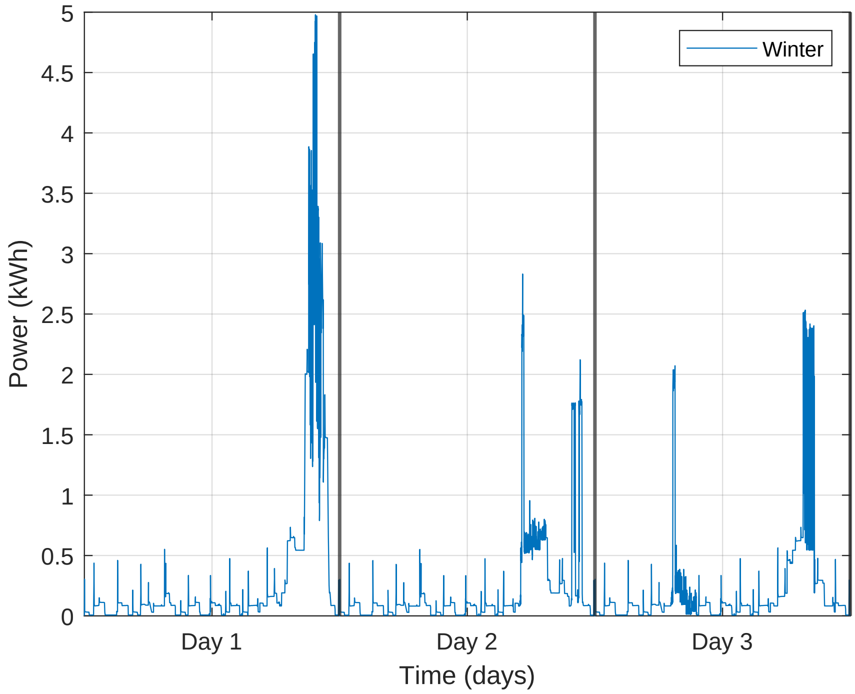


Figure 3.8 Load profile used for all days from October to March inclusive.

3.4 Summary

Chapter 3 evaluates the input data used in the simulations. This short presentations is accompanied by a brief analysis of the data. The results are presented and breifly discussed.

The test data involves the electricity price, weather, covering a four years period, i.e. from 2021 to 2024 and synthetically generated electricity consumption profiles.

4 Energy Management System (EMS)

The EMS, which controls the battery, is modelled in the following. First, a simple standard RBC is designed, which serves as a comparison for further control strategies tested.

4.1 Rule Based Control (RBC)

Figure 4.1 shows the flowchart of a traditional RBC, derived based on the available information from some commercial products. It charges/discharges whenever it can, and if the battery is full or empty, the MPPT controlling the Power coming from the PV is reduced or energy is imported from the grid, respectively.

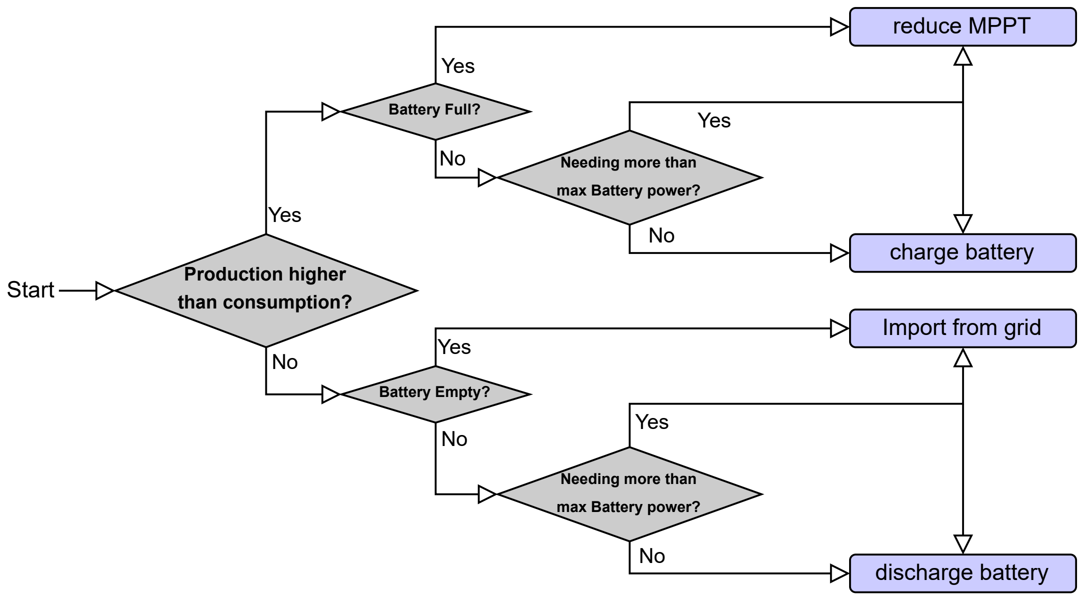


Figure 4.1 RBC flow chart.

4.2 Fuzzy-Logic Control (FLC)

The Fundamental of Fuzzy logic is to mimic artificial intelligence by applying linguistic rules that dictate decisions based on the status of a set of inputs. By weighting all active rules, the output is computed. This process is shown in Figure 4.2. The maximum rule space is decided by the amount of MF of each input. The resulting control Surface maps the FIS into a look-up table, which can then be deployed on microcontrollers, enabling rapid, light decision-making. For more details, please refer to [1, 40].

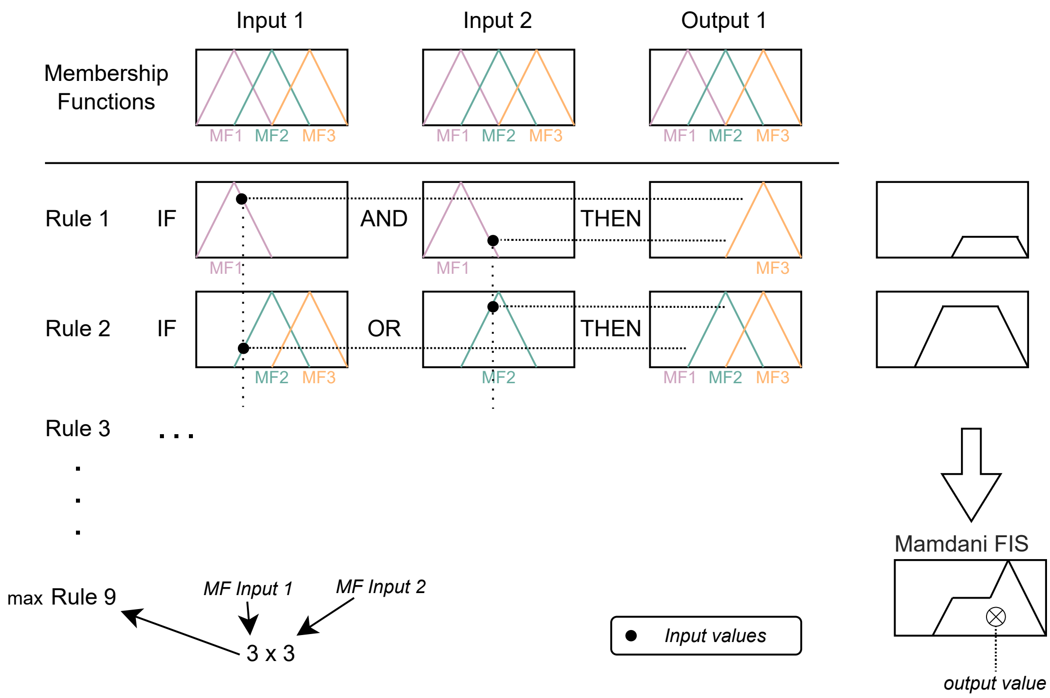


Figure 4.2 Fuzzy logic concept.

For the initial setup, a simple design has been chosen. The most crucial variables, such as the current SOE, the net power in the system and the electricity price, are used as control inputs. As with every development, there is a process of stages from the beginning to the end. If the initial Fuzzy Interference System (FIS) proved to be working as desired, a tuning process was applied to optimise the controller and push the limits.

The design process is shown in Figure 4.3.

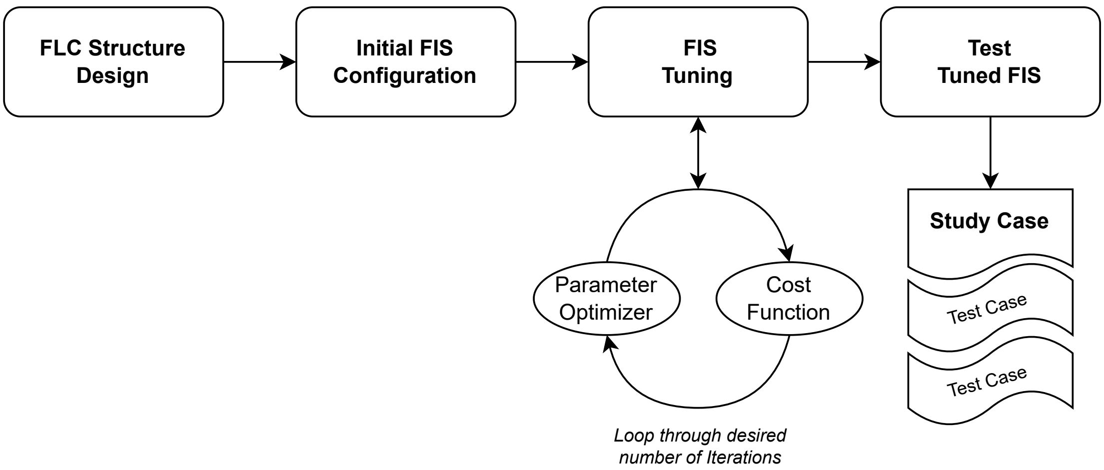


Figure 4.3 FLC development process.

4.2.1 FLC structure design

There are two structures that have been designed and analysed. The structure decides the number of inputs and outputs of the implemented FIS.

FLC Structure 1

The idea was to test whether a slow or "soft", always grid-connected charge and discharge of the battery would be better in the long term by decreasing the stress on the battery and thus increasing its lifetime. The inputs were chosen to be the SOE, net power (= Load - PV) and the electricity spot price. In order to make the FLC adaptive, the spot price is normalised over a horizon of 24 hours ahead. The output of the FIS is the requested battery power. For better clarity, few Membership Functions (MF) were created to keep the rule set within limits. Because the controller is known to be a soft control, it did not make decisions such as charge or discharge, but rather charge smooth with low C-rates. Therefore, the available PV power could not be fully captured.

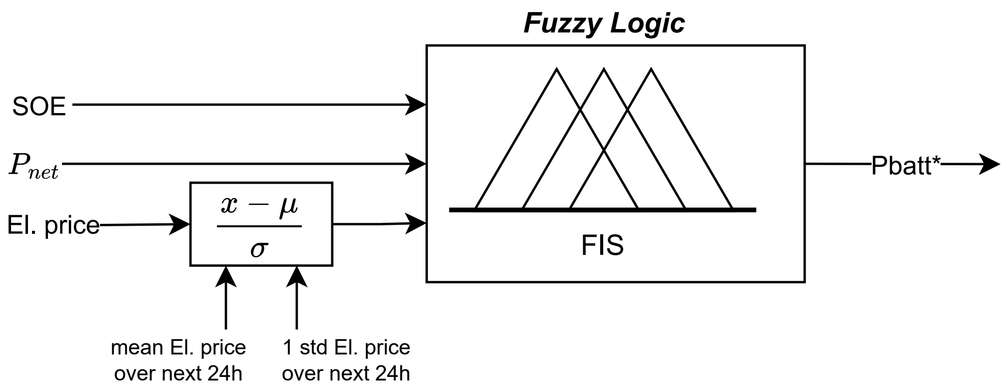
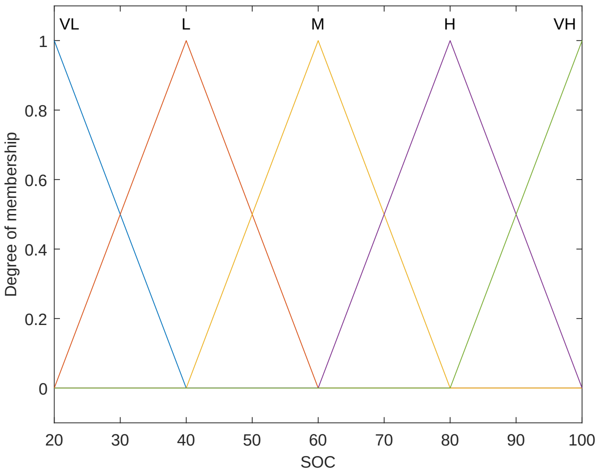


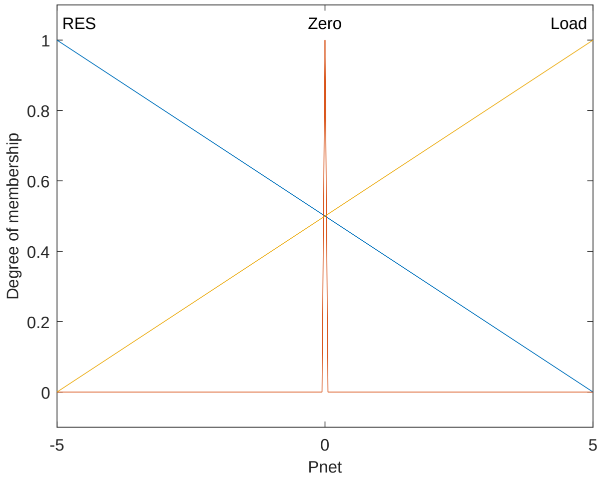
Figure 4.4 FLC structure 1.

Initial FIS Configuration

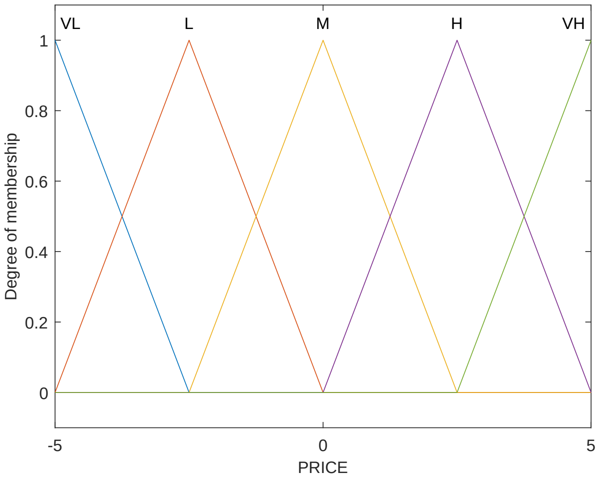
The MFs are displayed in Figure 4.5. The corresponding rule set can be found in the Appendix listed in Table A.3. The FIS is chosen in such way that charging from the grid is possible.



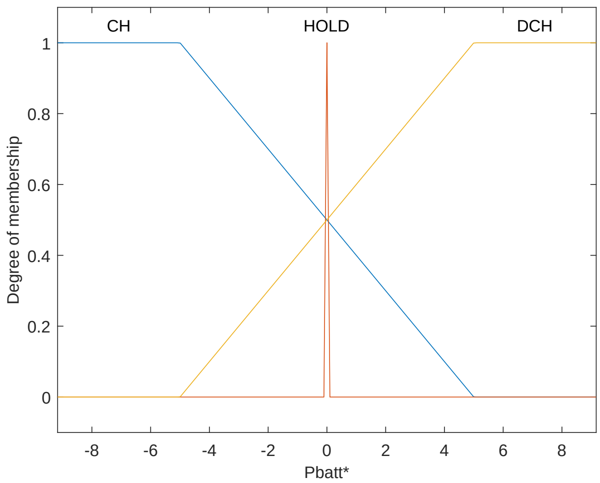
(a) MF of Input 1: SOC.



(b) MF of Input 2: net power.

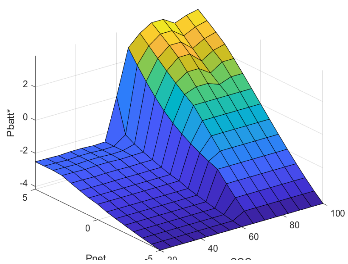


(c) MF of Input 3: standardised electricity spot price.

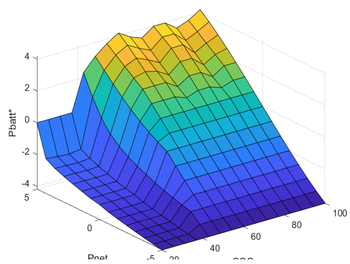


(d) MF of Output: battery power.

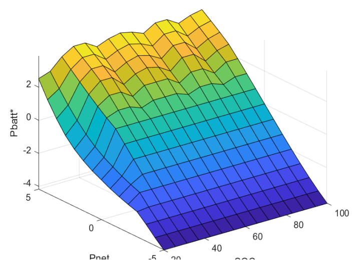
Figure 4.5 Membership functions of FIS used in FLC structure 1.



(a) Control surface for low (L) daily price.



(b) Control surface for medium (M) daily price.



(c) Control surface for high (H) daily price.

Figure 4.6 Control surface of FIS used in FLC structure 1.

FLC Structure 2

For the second structure, a different approach has been chosen. Instead of using the net power as an input, only the SOE and the electricity spot price are being used for the decision making. Narrowing down the decision space for the FLC to be only holding or discharging the battery makes the FIS smaller, simpler and faster. Now, if the PV is producing surplus power, the entire amount is used to charge the battery. And only if the PV cannot supply enough to cover the load, the FLC is asked whether the battery should be held in idling mode or be discharged. This makes use of the decision-making process of the FIS and converts the output into discrete battery action commands. The entire structure can be observed in Figure 4.7.

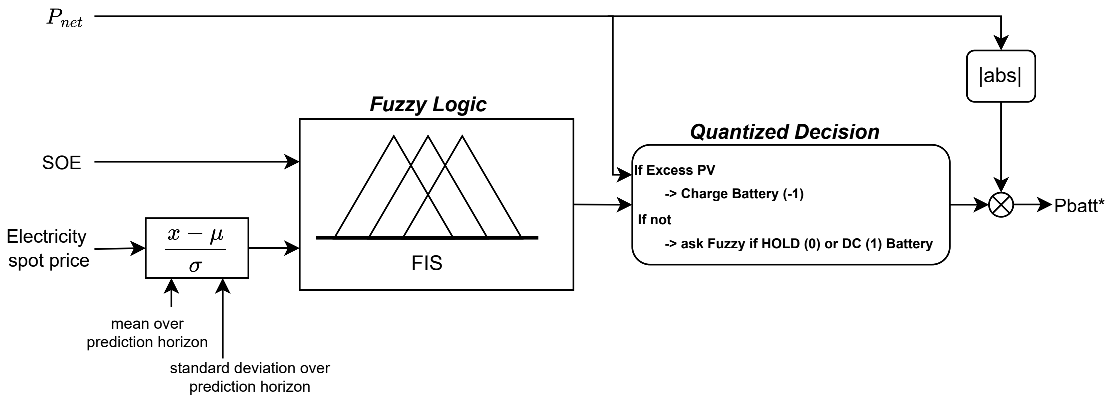
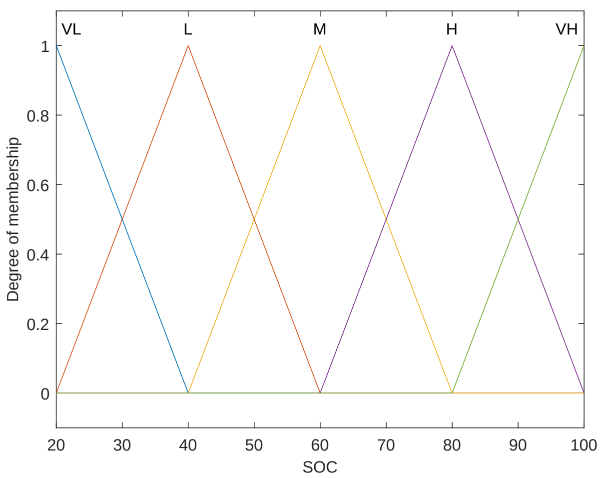


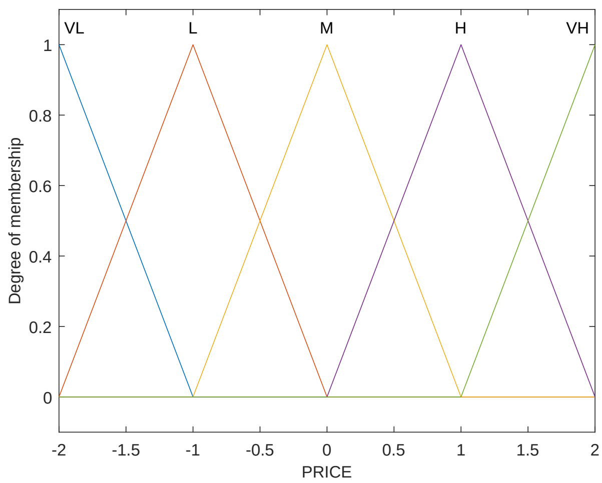
Figure 4.7 FLC structure 2.

Initial FIS Configuration

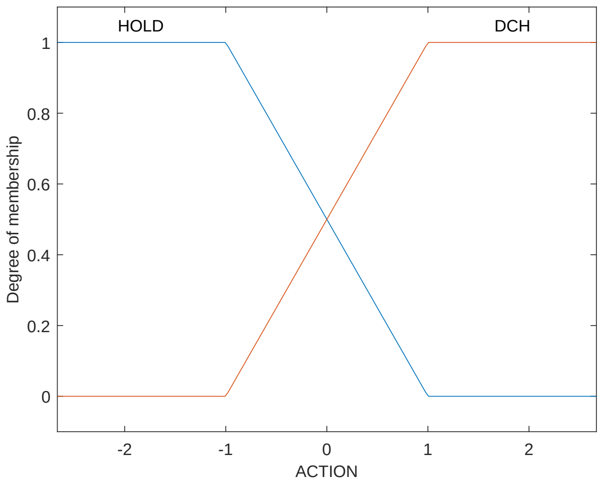
FLC Structure 2 only provides 2 separate inputs. The output only distinguishes between discharging (DCH) and idling (Hold) the Battery. As an initial set, 5 MF were chosen for each input and 2 for the output. The configuration is presented in Figure 4.8. The first two Figures 4.8a - 4.8b show the MF of the inputs, and Figure 4.8c shows the MF of the output. With two inputs and 5 MF functions each, a maximum of 25 rules can be defined. The rule set is listed in the Appendix in Table A.4, and the resulting control surface can be seen in Figure 4.8d.



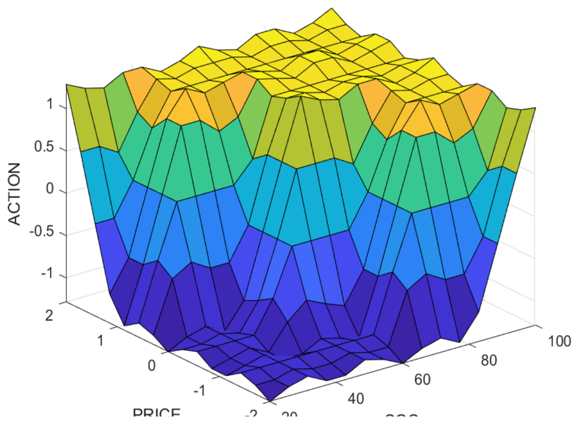
(a) MF of Input 1: SOE.



(b) MF of Input 2: electricity price.



(c) MF of Output: battery action.



(d) Control surface.

Figure 4.8 Membership functions and control surface of FIS used in FLC structure 2.

4.2.2 FIS Tuning

Using the initial FIS, the idea is now to optimise it. This can be done by tuning or learning. Tuning concentrates on adapting existing parameters within the MF of inputs and outputs, as well as modifying existing rules. Learning on the other hand focuses on adding new rules, for example when a FIS with an empty rule set is created or not all possible rules are defined yet. Because both tuning and learning are incredibly time-consuming, it is recommended to smartly initialise the system and only tune smaller parts of the system such as only specific inputs, MF or rules. Thus, in the following, only tuning was performed.

First, the desired, tunable settings are chosen. Tuning was conducted for the price input and the rules, in two independend processes. Then optimisation algorithms such as Genetic Algorithm (GA), Parentsearch or Particle swarm optimization (PSO) are used to modify chosen parameters and rules. After each iteration, a cost function is called, which tests the newest result. If no new global minimum is found, the tuning process starts over again.

Both approaches, tuning the membership functions of the input as well as the ruleset separately, have not achieved noteworthy results. The differences compared to the initial FIS have been negligible. Further approaches of tuning using real full-year data sets will follow in future work.

4.3 Summary

Chapter 4 explained the design steps of the RBC as well as both FLC structures.

Moving from the FLC structure design via the initial FIS configuration and the FIS tuning process, this chapter covers the entire design of the EMS controls.

5 HEMS Assessment Results

5.1 Study Case: RBC vs FLC

This case study compares the RBC to both presented FLC structures. The hope is to see differences within the lifetime, profit, amortisation time, LCOS etc. Figure 5.1 give an overview over the conducted Tests.

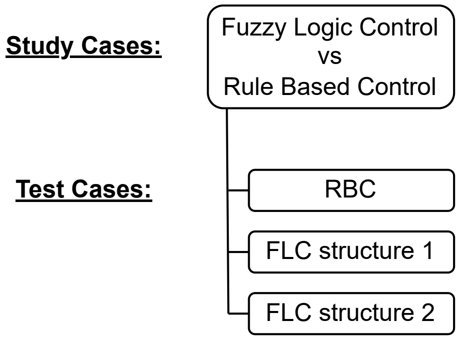


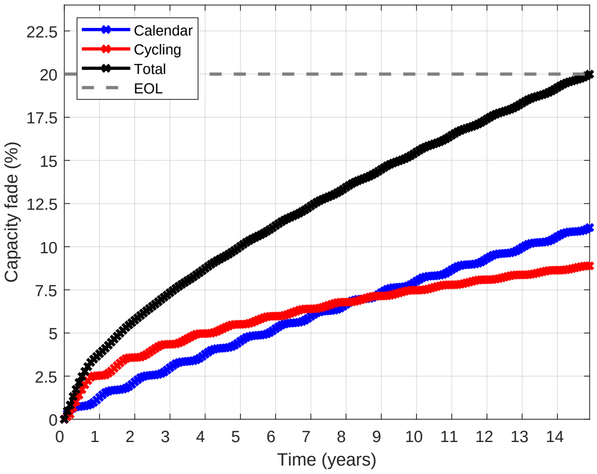
Figure 5.1 Study case and test cases.

To analyse the behaviour of the controllers, different aspects of the battery usage have been visualised. For each test case, in the following Sections 5.1.1 - 5.1.3, five graphs have been generated each.

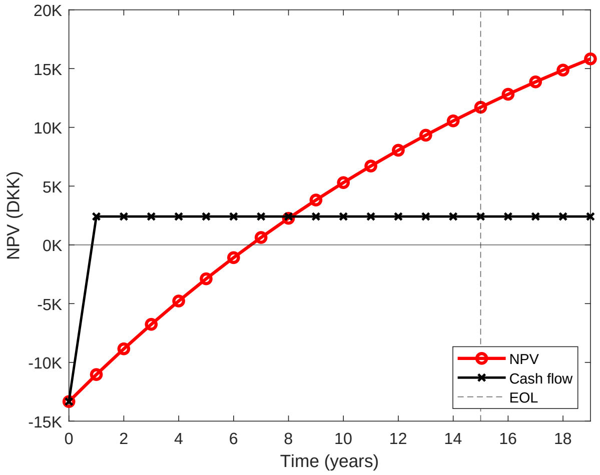
(a) Capacity fade until end of life
(b) NPV until end of life
(c) Idling vs cycling time over one entire year
(d) Idling time over different SOE levels
(e) Cycle count over SOE levels and cycle depths

These figures help describe the behaviours and explain the results.

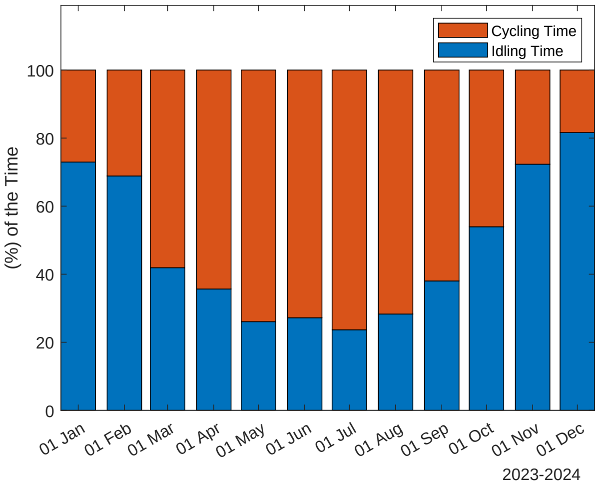
5.1.1 RBC



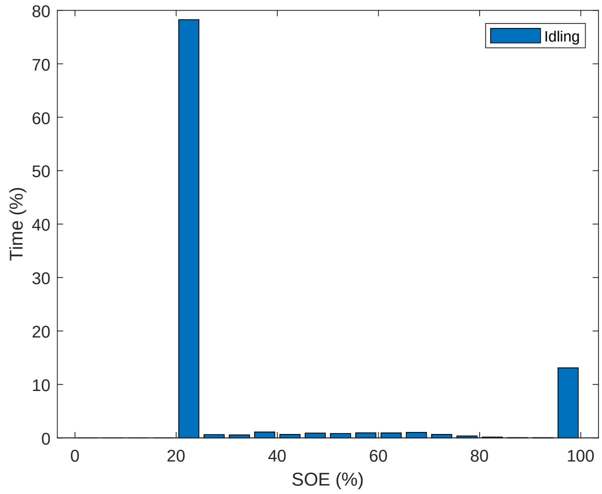
(a) RBC: Battery Lifetime.



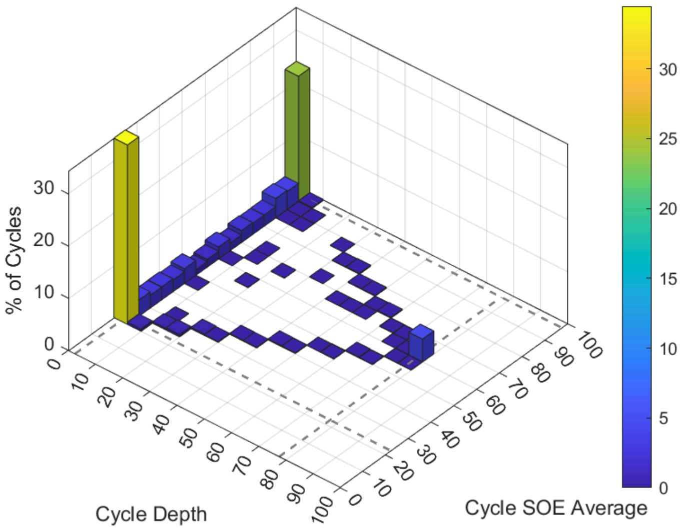
(b) RBC: NPV.



(c) RBC: Idling vs Cycling Time.



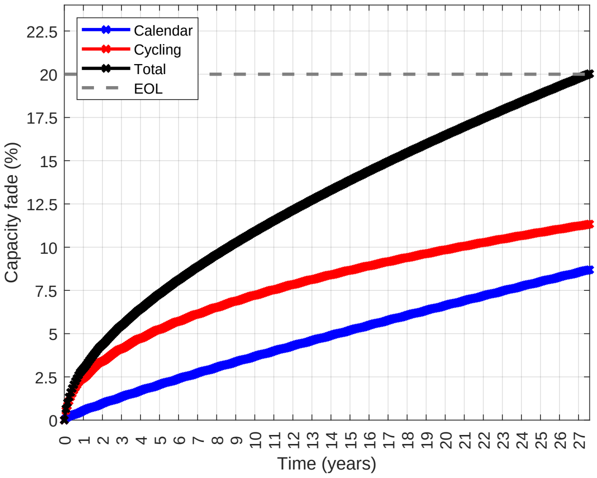
(d) RBC: Idling times at SOE levels.



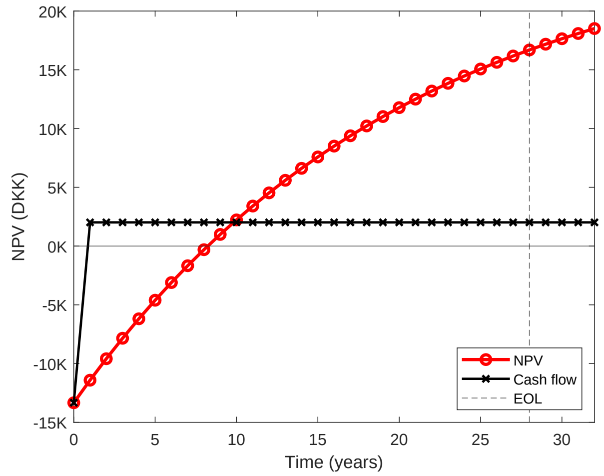
(e) RBC: Cycle Count at SOE levels and cycle depths.

Figure 5.2 RBC: results.

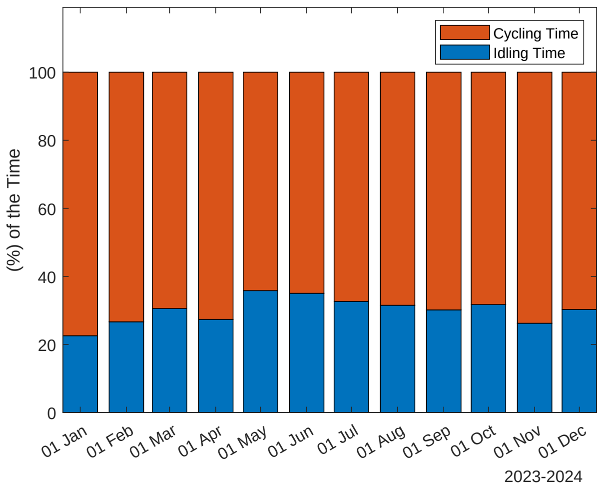
5.1.2 FLC structure 1 - soft control



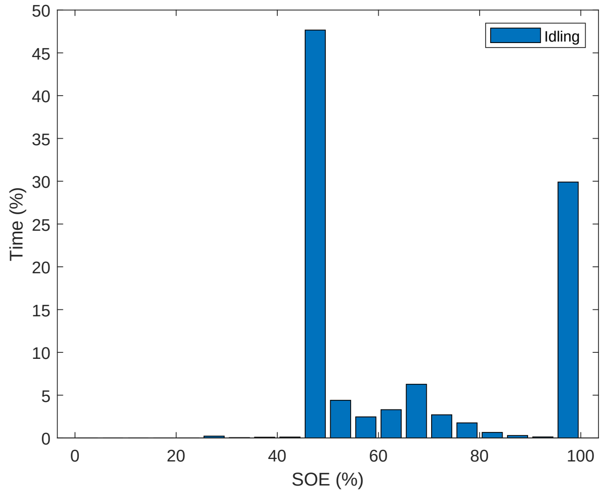
(a) FLC 1, Battery Lifetime.



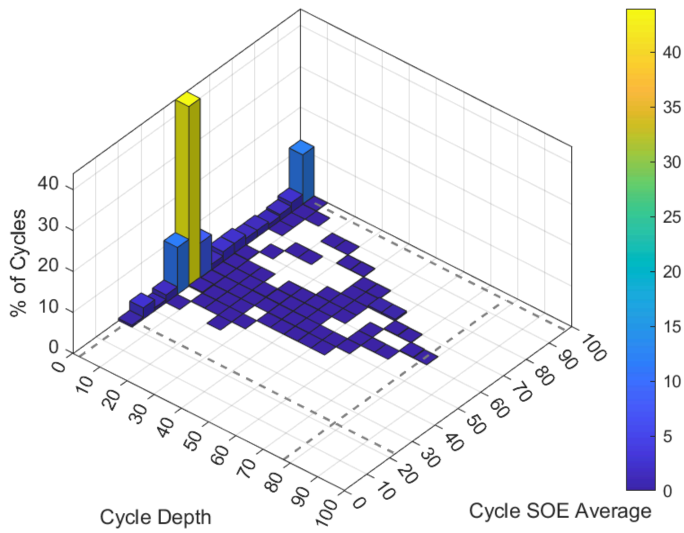
(b) FLC 1, NPV.



(c) FLC structure 1: Idling vs Cycling Time.



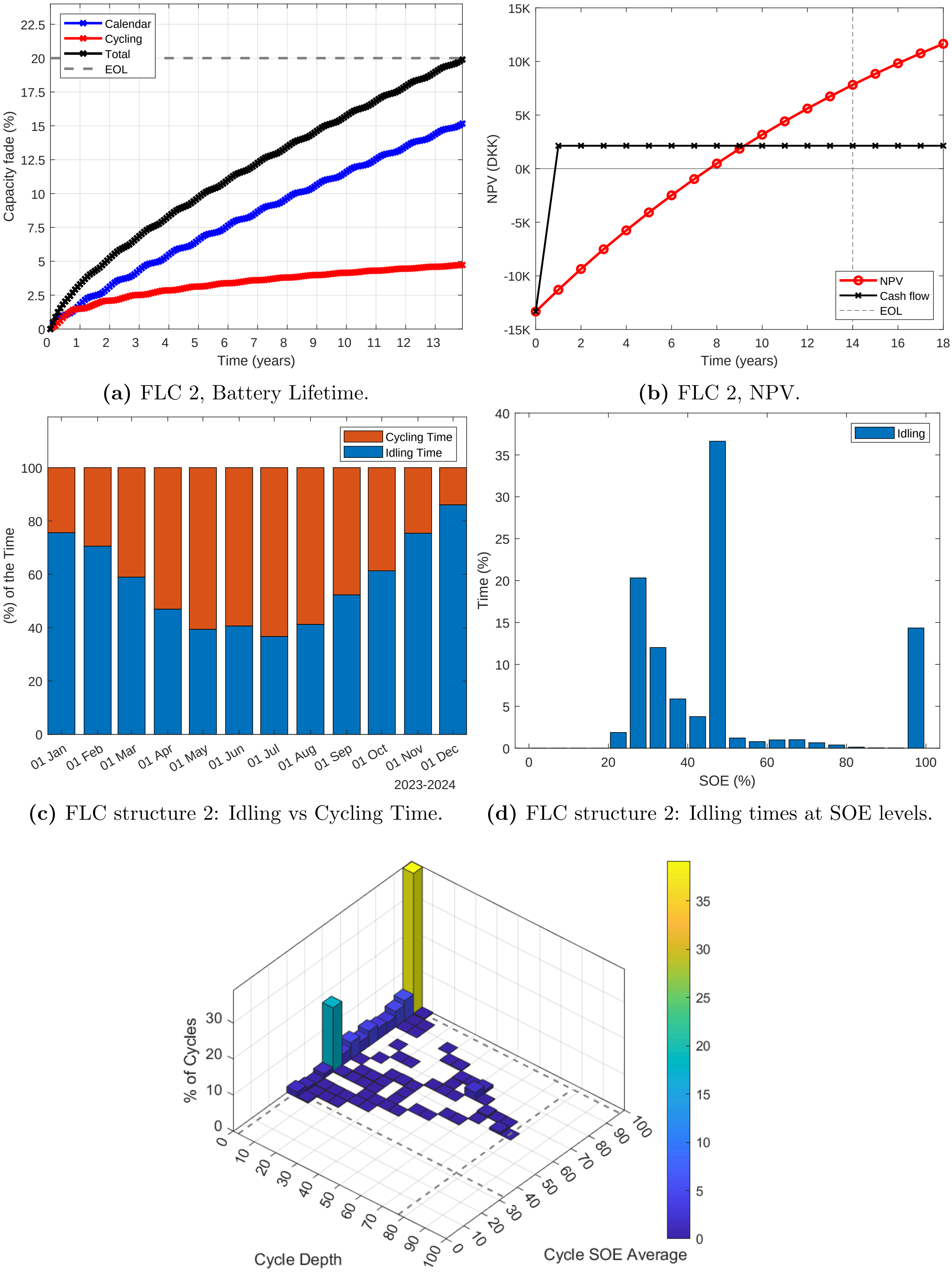
(d) FLC structure 1: Idling times at SOE levels.



(e) FLC structure 1: Cycle Count at SOE levels and cycle depths.

Figure 5.3 FLC structure 1: results.

5.1.3 FLC structure 2 - discrete control



(a) FLC 2, Battery Lifetime.

(b) FLC 2, NPV.

(c) FLC structure 2: Idling vs Cycling Time.

(d) FLC structure 2: Idling times at SOE levels.

(e) FLC structure 2: Cycle Count at SOE levels and cycle depths.

Figure 5.4 FLC structure 2: results.

5.1.4 Comparison

In the following the controls are compared side by side. Table 5.1 list all yearly energies statistics in kWh. Table 5.2 compares all the resulting calculations over the full lifetime of the battery. And Table 5.3 presents the final electricity costs for a single year. For the following, the cost for electricity from PV is set to 0.3 DKK/kWh [41]. The total bill consists of all final costs, including the electricity bill, the charging cost from PV, and the battery discharging cost.

	RBC	FLC 1:	FLC 2:
Energy used	2178	2178	2178
Grid import	1008	1240	1156
Grid export	9	5.2	5.8
PV available	1998	1998	1998
PV used	1261	1037	1093.8
PV excess	736	961	905
Load not covered by PV	1725	1725	1725
Battery throughput	1573	1756	1245

Table 5.1 Yearly energy statistics in kWh.

	RBC	FLC 1:	FLC 2:
Lifetime (years)	17.2	27.6	13.9
Battery throughput (kWh)	23605	49181	17433
LCOS (DKK/kWh)	1.72	1.08	2.28
NPV (at 10 years)	5297	2226	4230

Table 5.2 Lifetime statistics.

	RBC	FLC 1:	FLC 2:
El bill without HEMS	4425	4425	4425
El bill with HEMS	2012	2410	3493
Battery DC cost	1181	894	1345
total Bill	3674	3615	3962

Table 5.3 Yearly cost statistics in DKK.

5.2 Discussion

According to the battery lifetime model, the soft-controlled FLC Structure 1 demonstrates promising performance. However, the estimated battery lifetime appears to be overestimated and may not accurately reflect real-world conditions. The analysis indicates a battery lifetime increase of 85.2% compared to the RBC. While the absolute values should be interpreted cautiously, the relative improvement over both the RBC and the discretely controlled FLC suggests the general trend is reliable. The amortisation time of the Net Present Value (NPV)—defined as the point in time when the NPV becomes positive—appears similar across configurations. Although the RBC becomes economically viable after less than seven years, the extended battery lifetime of FLC Structure 1 results in a higher overall economic benefit over the full lifespan.

In terms of operational patterns, rule-based control (RBC) predominantly charges from photovoltaic (PV) sources, extending idling periods during winter, as expected. Consequently, the mean state of energy (SOE) during idling for RBC is approximately 20%, indicating the battery remains mostly empty. In contrast, FLC Structure 1 exhibits a higher mean idling SOE level, typically in the range of 45–50%. The cycling behavior also differs significantly. For FLC Structure 1, the cycling activity is concentrated within the 45–50% SOE range, with shallow cycle depths (0–5%). Additionally, the number of cycles in the high SOC range (95–100%) is reduced. These operational characteristics likely contribute to the extended estimated battery lifetime observed for FLC Structure 1.

Figure 5.5 presents the Levelized Cost of Storage (LCOS) and NPV results. The lowest LCOS is achieved by FLC Structure 1, primarily due to its high energy throughput and extended operational lifetime. Meanwhile, the RBC shows the highest NPV at the 10-year mark. However, when evaluating the NPV over the entire lifetime of the battery, FLC Structure 1 demonstrates superior economic performance.

FLC Structure 2 performs poorly across all evaluated metrics. Despite exhibiting a higher utilisation of PV energy and a lower grid import than FLC Structure 1, it does not perform well in terms of LCOS, NPV, or battery lifetime.

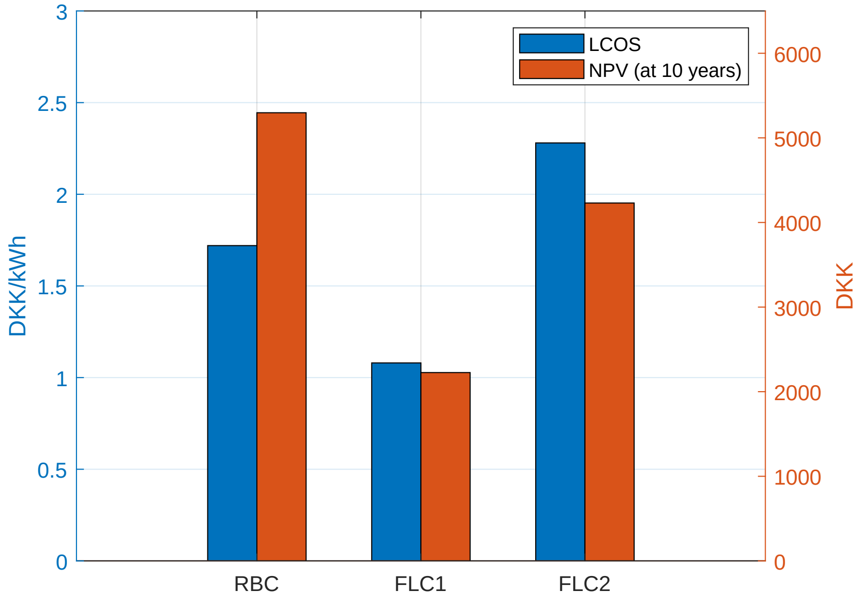


Figure 5.5 Final comparison of the economic metrics.

Radar charts, such as Figure 5.6, are well suited for providing a visual comparison of multiple performance metrics. To facilitate a clearer overview, the data have been normalised. The plot effectively highlights the differences between the control strategies. Notably, the RBC performs strongly in maximising PV energy utilisation and minimising the import of energy from the grid.

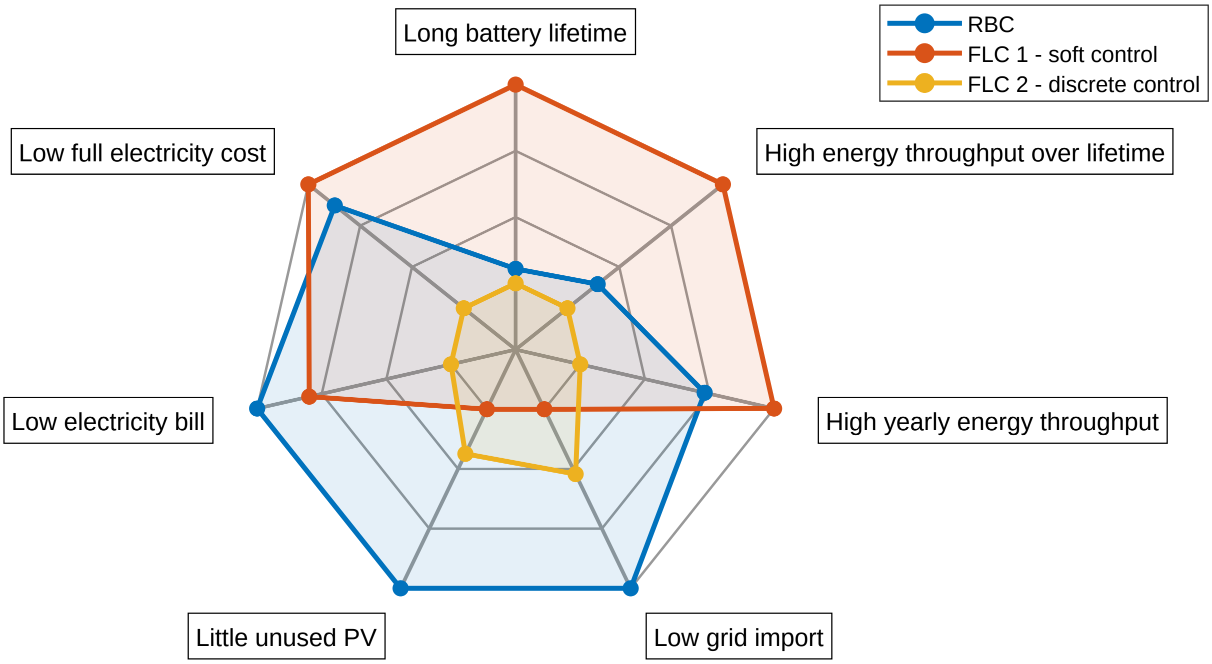


Figure 5.6 Final qualitative comparison.

5.3 Summary

Chapter 5 tested the implemented control structures and compares them side by side. The results are visually presented and discussed. First, the RBC results are shown, then the FLC structures 1 and 2 follow.

The final comparison consists of a radar chart, visualising multiple performance metrics. This is a helpful step towards the easy assessment of the controls.

6 Conclusion

6.1 Summary of the Work

Following the development and testing of a FLC for a HEMS, it can be concluded that the proposed EMS is effective in prolonging battery lifetime. This conclusion is drawn under the assumption that, while the employed lifetime model may not yield fully realistic absolute lifetime values, it is sufficiently robust to illustrate relative differences in battery usage and degradation patterns across control strategies. Quantitatively, the service life increased by an impressive 85% compared to the RBC strategy.

It is acknowledged that the economic gains, particularly in terms of profit margin, are marginal, reaching about 1.5%. Nonetheless, the proposed FLC approach offers additional advantages, including robustness, operational smoothness, algorithmic simplicity, human interpretability, and being computationally lightweight.

Looking forward, better economic performance may be achieved through the use of more advanced control strategies. In particular, approaches that include load and weather forecasts over a defined prediction horizon and optimise charging and discharging behaviour within a control horizon are likely to yield better results in terms of profit maximisation and energy utilisation.

6.2 Future Work

For future research, the developed test environment provides an optimal foundation for evaluating additional energy management strategies and system designs. It enables consistent and controlled comparisons across different approaches.

Further investigation into the tuning process is recommended. Additionally, exploring alternative FLC structures with an extended set of input variables may yield improved control outcomes.

It is also advisable to test the system using a broader set of case studies, including data from different years and scenarios with extreme conditions, to conduct rigorous limit testing and assess generalizability.

Finally, the test environment should be utilised to assess and benchmark emerging energy management systems (EMS), with a dual focus on maximising battery longevity and ensuring economic viability.

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A Appendix

A.1 LCOS Derivation

The following proof is taken from [35, p.30] This shows the derivation of the LCOS from the NPV.

$$\text{NPV} = 0 \tag{A.1}$$

$$\text{NPV of cost} = \text{NPV of remuneration} \tag{A.2}$$

$$\sum_{n}^{N} \frac{\text{cost}(n)}{(1+r)^n} = \sum_{n}^{N} \frac{\text{remuneration}(n)}{(1+r)^n} \tag{A.3}$$

$$\sum_{n}^{N} \frac{\text{cost}(n)}{(1+r)^n} = \sum_{n}^{N} \frac{E_{\text{out}}(n) \cdot \text{LCOS}}{(1+r)^n} \tag{A.4}$$

$$\sum_{n}^{N} \frac{\text{cost}(n)}{(1+r)^n} = \text{LCOS} \cdot \sum_{n}^{N} \frac{E_{\text{out}}(n)}{(1+r)^n} \tag{A.5}$$

$$\text{LCOS} = \frac{\sum_{n}^{N} \frac{\text{cost}(n)}{(1+r)^n}}{\sum_{n}^{N} \frac{E_{\text{out}}(n)}{(1+r)^n}} \tag{A.6}$$

where NPV stands for Net present value, n the year, r the discount rate, N lifetime in years E_{out} the Electricity discharged in year n and $LCOS$ the constant price for electricity discharged. The result shows that not only the cost but also the discharged energy needs to be discounted.

A.2 PV model in detail

A.2.1 PV Model

The equations embedded in the PV model, used to calculate the PV Power Production are shown below:

$$T_{pv} = T_a + \left(\frac{G}{800}\right) \cdot (\text{NOCT} - 20) \tag{A.7}$$

$$V_{out} = V_{max} \cdot \left(1 + c \cdot (T_{ref} - T_{pv}) + \ln\left(1 + b \cdot \left(\frac{G}{1000} - 1\right)\right)\right) \tag{A.8}$$

$$I_{out} = I_{max} \cdot \left(\frac{G}{1000}\right) \cdot (1 + a \cdot (T_{ref} - T_{pv})) \tag{A.9}$$

$$P_{out} = \frac{V_{out} \cdot I_{out}}{P_{max}} \cdot P_{nom} \tag{A.10}$$

$$\tag{A.11}$$

Conceptual Summary:

Name	Description	Unit
T_a	Ambient temperature	°C
G	Solar irradiance	W/m²
$NOCT$	Nominal Operating Cell Temperature	°C
V_{max}	Voltage at max power	V
I_{max}	Current at max power	A
T_{ref}	Reference temperature	°C
a, b, c	Temperature and irradiance coefficients	-
P_m	Max power	W
P_{nom}	Nominal power	W

Table A.1 PV parameter descriptions and units

Name	Description	Unit
T_{pv}	*Panel temperature*: Simulates how hot the panel gets based on sunlight.	°C
V_{out}	*Panel Voltage*: Decreases with heat and adjusts slightly with light level.	V
I_{out}	*Panel Current*: increases with light but drops with panel heating.	A
P_{out}	*Panel Relative Power Output*: fraction of the nominal Power.	%/100

Table A.2 PV parameter explanations and units

A.2.2 Validation figures

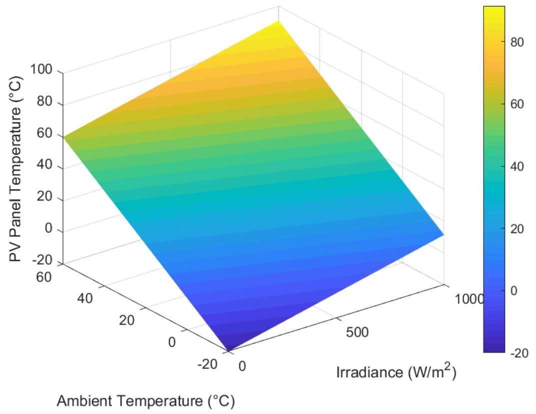

Figure A.2.1 PV Module Temperature vs. Irradiance and Ambient Temperature.

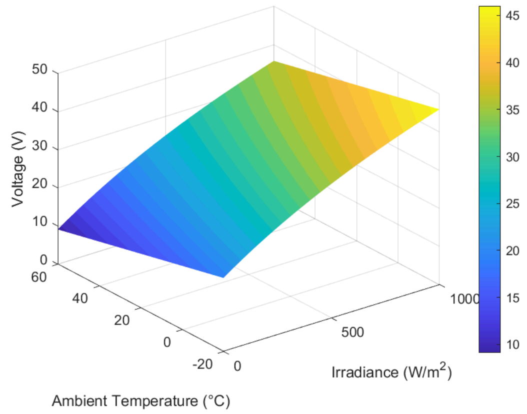

Figure A.2.2 Output Voltage vs. Irradiance and Ambient Temperature.

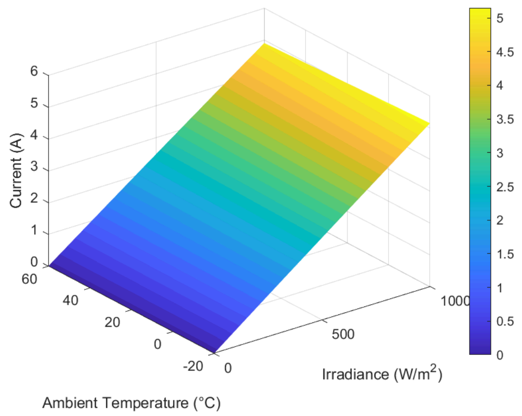

Figure A.2.3 Output Current vs. Irradiance and Ambient Temperature.

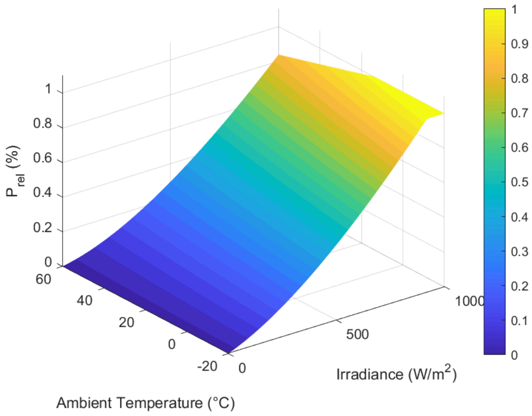

Figure A.2.4 Relative output power vs. irradiance and ambient temperature.

Scaling the relative output power with an exemplary Peak Power of 6MW, the resulting power at certain Iradiation values and Temperatures can be seen in Figure A.2.5 and A.2.6.

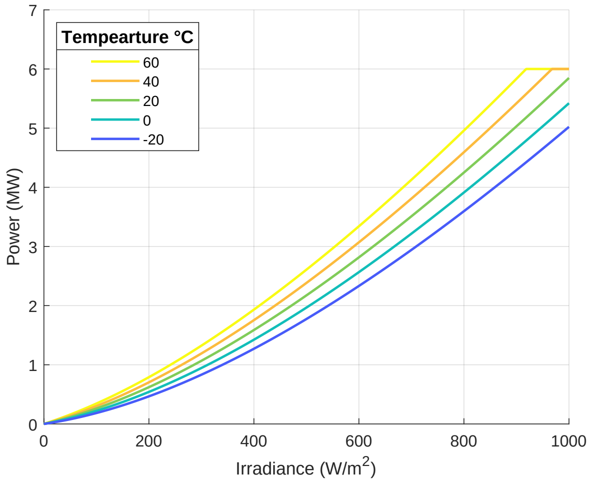

Figure A.2.5 Output Power vs. Irradiance in specific Ambient Temperature levels.

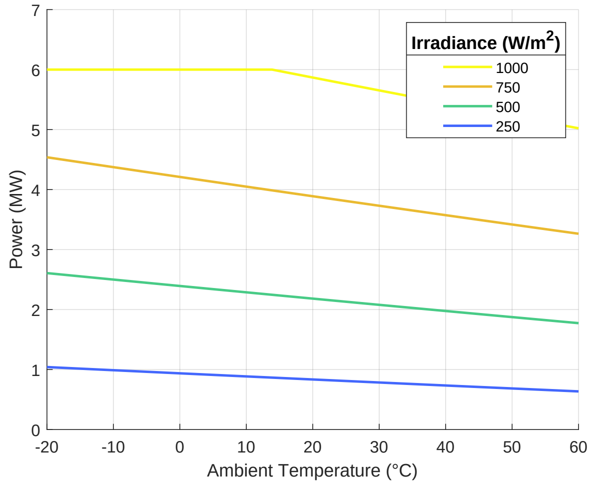

Figure A.2.6 Output Power vs. Temperature with specific Irradiance levels.

A.3 FIS Rule sets for each FLC structure

A.3.1 FLC Structure 1

SOC	Pnet	PRICE	Pbatt*
ANY	RES	ANY	CH
ANY	Zero	ANY	HOLD
VL	Load	VL	CH
L	Load	VL	CH
M	Load	VL	HOLD
H	Load	VL	HOLD
VH	Load	VL	DCH
VL	Load	M	HOLD
L	Load	M	HOLD
M	Load	M	DCH
H	Load	M	DCH
VH	Load	M	DCH
VL	Load	VH	DCH
L	Load	VH	DCH
M	Load	VH	DCH
H	Load	VH	DCH
VH	Load	VH	DCH
VL	Load	L	HOLD
L	Load	L	HOLD
M	Load	L	HOLD
H	Load	L	DCH
VH	Load	L	DCH
VL	Load	H	HOLD
L	Load	H	DCH
M	Load	H	DCH
H	Load	H	DCH
VH	Load	H	DCH

Table A.3 Initial rule set for FLC structure 1 .

A.3.2 FLC Structure 2

SOC	PRICE	ACTION
VL	VL	HOLD
VL	L	HOLD
VL	M	HOLD
VL	H	HOLD
VL	VH	DCH
L	VL	HOLD
L	L	HOLD
L	M	HOLD
L	H	DCH
L	VH	DCH
M	VL	HOLD
M	L	HOLD
M	M	DCH
M	H	DCH
M	VH	DCH
H	VL	HOLD
H	L	DCH
H	M	DCH
H	H	DCH
H	VH	DCH
VH	VL	DCH
VH	L	DCH
VH	M	DCH
VH	H	DCH
VH	VH	DCH

Table A.4 Initial rule set for FLC structure 2 .

A.4 Time Signals

The complete Time signals of different test szenarios are displayed here.

A.4.1 RBC 2024

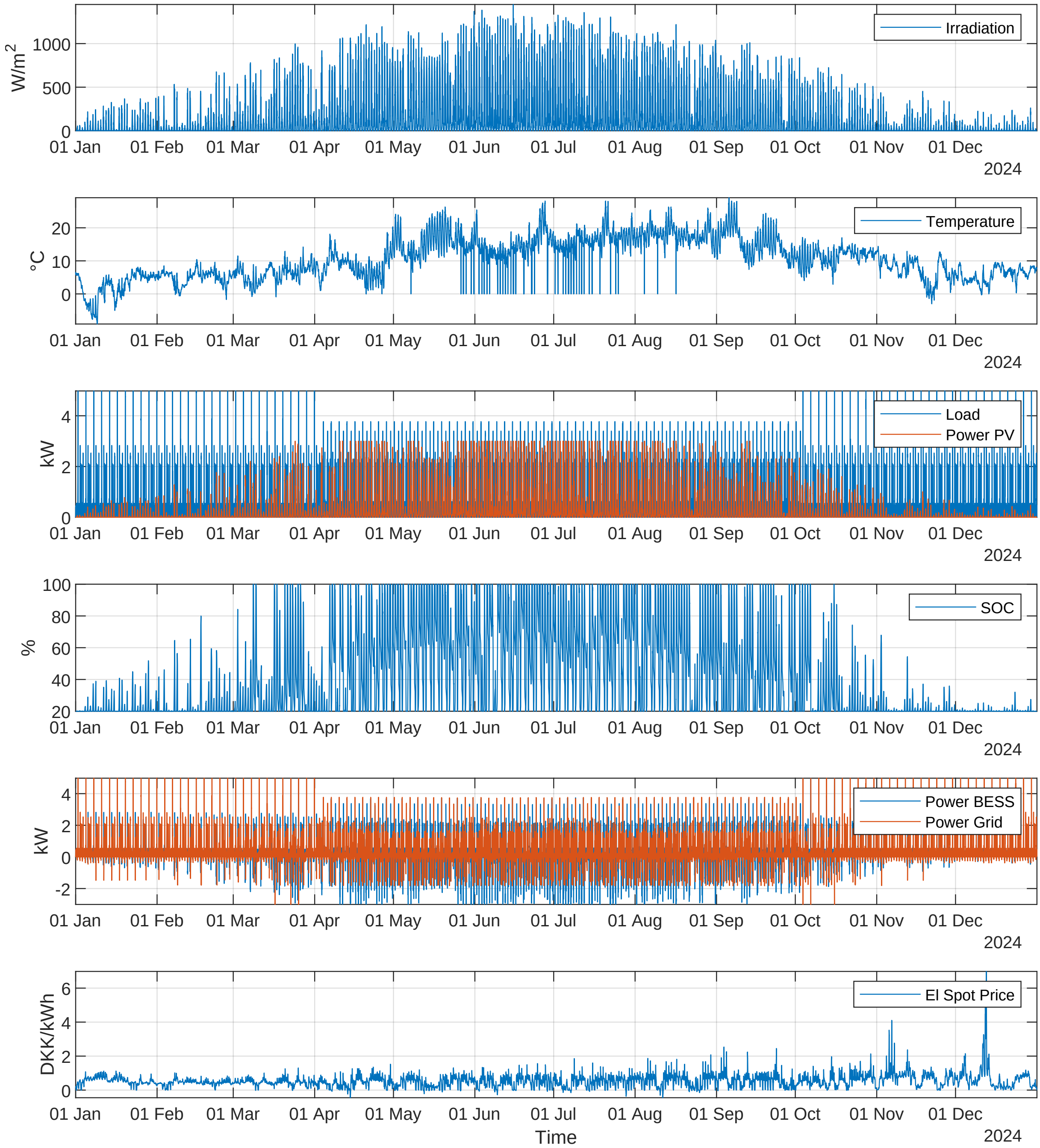

Figure A.4.1 Simulation Monitoring RBC 2024.

A.4.2 FIS structure 1 2024

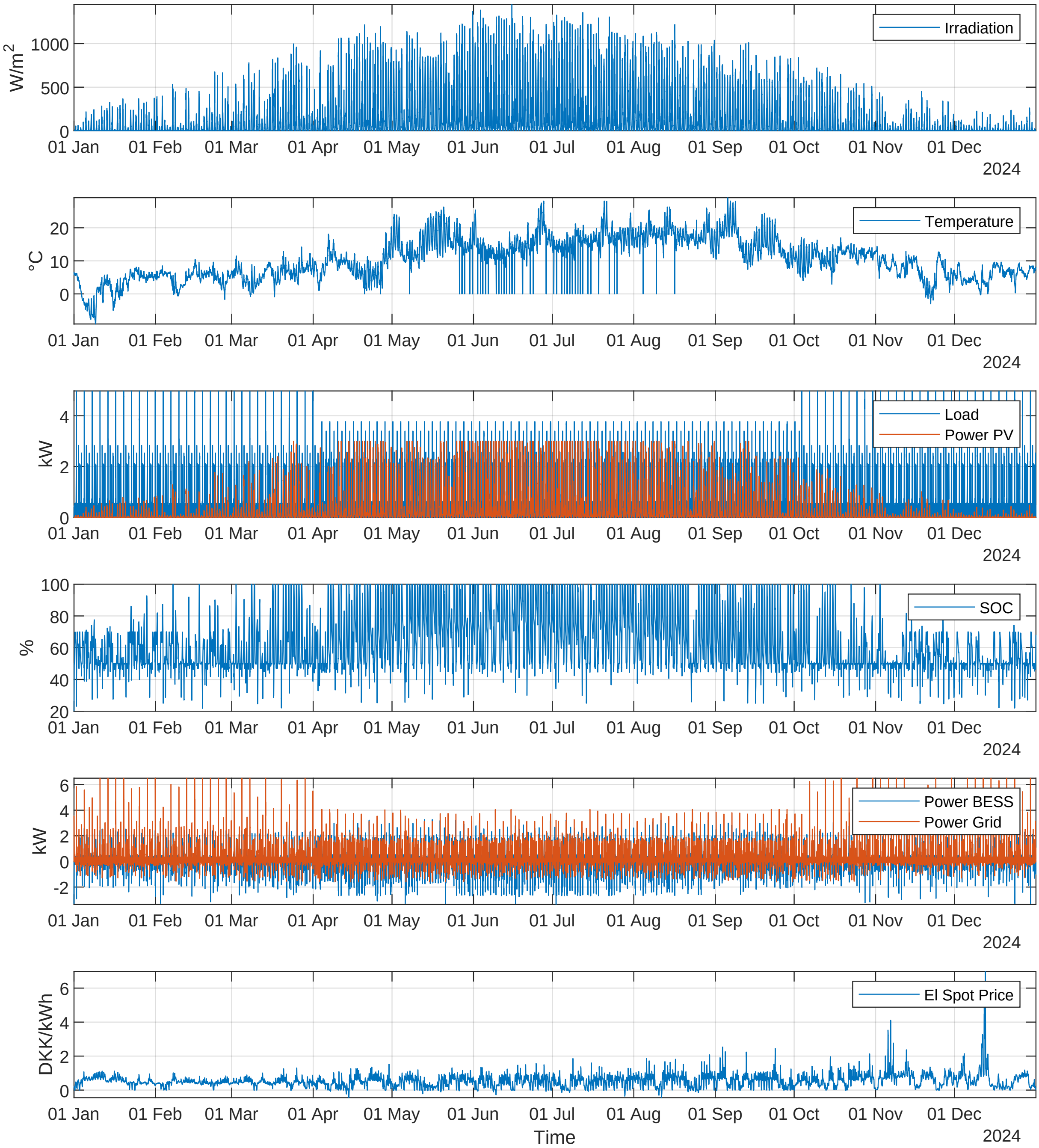

Figure A.4.2 Simulation Monitoring FIS structure 1 2024.

A.4.3 FIS structure 2 2024

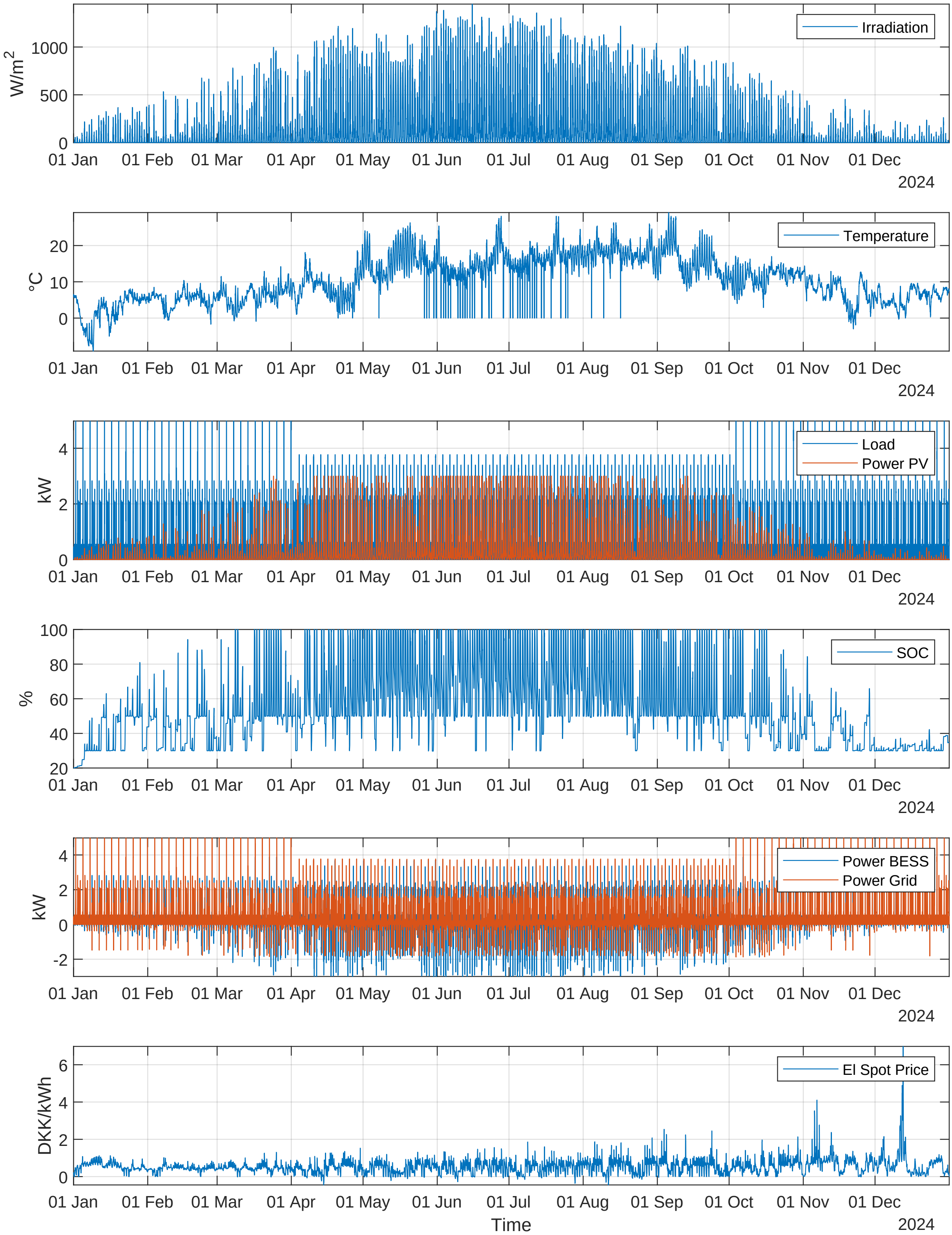

Figure A.4.3 Simulation Monitoring FIS structure 2 2024.