Framework for Battery Life Time Estimation on Prosumers Applications

- Master Thesis -

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Abstract:

The current fluctuations observed in energy prices in the post-covid period energy markets and the disappearance of the payment of energy delivered to the grid affected severely prosumers profitability. Now, every wrong estimation and lack of accuracy becomes decisive when estimating the return on investment of prosumers' installation. This project investigates the main factor that could cause potential deviations from estimations and proposes a correction method based on the sampling time. As well, it provides a counter-example of a pseudo-optimized scenario and proposes a guideline to evaluate the cost-effectiveness of an Energy Management System.

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Acknowledgement

We owe deep gratitude to our friends and family. Especially to the ones who are not here anymore. You will be remembered, loved and missed. Your legacy will be carried proudly and your memories will burn lively. The pain will hopefully leave, but your smile will feed forever the warmth of our hearts.

Anoy & Petra, August 16, 2023

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Chapter 1

Introduction

The following sections delve into the research and motivation behind the work. Background and Motivation of the project are introduced, followed by the Problem Formulation, Objectives, and the State of the Art. Finally, the Scope with its Limitations is presented.

1.1 Background

Climate change is one of the major global challenges the world faces today. According to NASA, in the last 20 years, 19 have been the warmest ever recorded.[1] The impact of climate change is already evident in many forms such as the shrinking of the arctic sea ice, rising sea levels and extreme weather events. For example, over the course of the last century, the average temperature rose by 0.98°C. Without any endeavors to reduce carbon emissions, the effects of global warming will worsen and the temperature is expected to rise by a tremendous 1.5°C by 2050.[2]

Power generation is one of the main causes of climate change. Generating electricity and heat by burning fossil fuels has a major contribution to climate change accounting for over 75% of global greenhouse gas emissions and nearly 90% of all carbon dioxide emissions.[3] To mitigate this problem, installed renewable capacity needs to triple by 2030. Using renewable energy resources rather than fossil fuels to generate electricity reduces greenhouse gas emissions from the power sector and contributes to climate change mitigation. For example, photovoltaic solar systems (PV) and wind turbines (WT) have increased significantly in recent years and their installed capacity reached 3,500,000 MW in 2023. [4]

While renewables are less polluting than fossil fuel generators in terms of emissions, power supply from renewable sources is dependent on variable natural resources, making them unpredictable and unable to provide a steady source of energy. To mitigate this issue, energy storage systems are implemented to balance consumption with production in both grids and micro-grids. For this reason, hybrid power systems of wind turbines, solar panels and energy storage are a common solution to contribute to cost reduction as well as to the increase in overall system economic profit.

According to the Danish Energy Agency, the average wholesale electricity price in January 2023 was 107.6 euros per megawatt-hour, down nearly seven per cent from January 2022. A number of factors have contributed to the rise in electricity prices in Europe since 2021, including a drop in wind power generation due to low wind speed, increased heating demand due to cold winters, and increases in natural gas and coal prices depicted in Figure 1.1.[5]

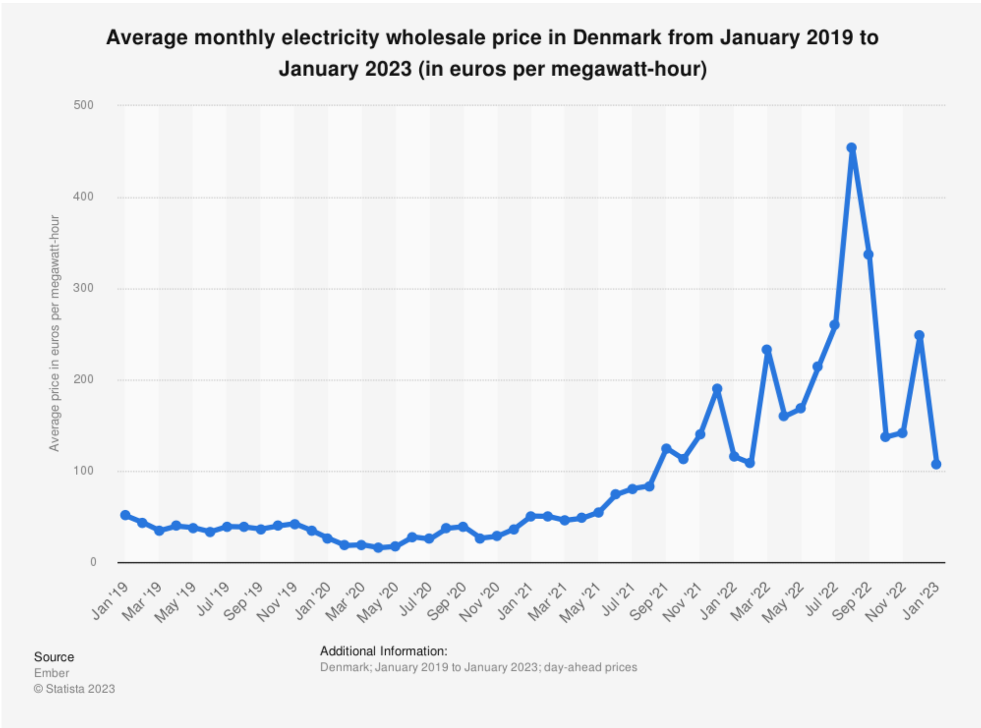

Figure 1.1: Average Monthly Wholesale Price in Denmark in the last 4 years [6]

Due to the unstable prices of energy and other essential commodities, a growing number of consumers are now considering becoming *prosumers* - consumers with local generation.[7]

This trend has been fueled by a combination of factors, including the rise of renewable energy technologies, the increasing availability of affordable energy storage solutions, and a desire among consumers to take control of their own energy use and reduce their reliance on traditional energy providers.[8] By becoming prosumers, these individuals not only gain greater energy independence and flexibility, but they also contribute to a more sustainable and resilient energy system overall. As such, the trend towards prosumption is likely to continue to grow in the years ahead, as more and more people recognize the benefits of taking charge of their own energy use.[9]

The incentives invested on wind technology considerably solidified the wind industry.

Initially, bellow 50kW of rated power was considered *small wind turbine* but soon 3-15 kW becomes as well attractive.[10] Combined with the unstable energy market and its corresponding increase of energy price; the threshold has lowered for consumers who would potentially benefit from reducing their energy consumption expenses within a scaled investment to become prosumers.[11] Sequentially, a similar evolution were followed by the solar energy industry.[12] Moreover, solar energy exhibits some complementary behaviour with wind generation since the "trough" of one corresponds with the "peaks" of the other.[13]
Prosumers have a *Net Metering* or *Feed-in-Tariffs* whose returns are significantly lower than energy producers. That is why their main focus is to minimize energy exchange with the grid. In order to maximize self-consumption or minimize interaction with the grid, a battery energy storage system (BESS) and a proper energy management system (EMS) are required.

Currently, both industrial and research Energy Management Systems targeting prosumers focus on minimizing the electricity bill. They use metrics such as self-consumption ratio (energy self-consumed divided by the total energy consumed).[14] Usually it is taken into account the effect of local generation, fixed load, and BESS. However, it can only match the economic interests of the prosumer by also quantifying the operational costs (as assets degradation).

The energy storage unit is the component with the shortest useful lifespan. The most vulnerable component to the user decision and architecture (renewable integration). Authors in [15] exhibit differences up to 20% of end-of-life time acceleration when the operational conditions differ from the standard ones. Its degradation follows complex behaviours (ageing and idling) that require moderate computational resources and they are often linearized for EMS decision-making processes.

1.2 State of Art

The actual distribution of prosumers in Europe is unknown, but it is estimated that almost a quarter of electricity consumption (680 TWh) could be covered by prosumers in 2050.[16].

Table 1.1: Types of Lithium Batteries

Type and Chemical Structure	Applications	Capacity and Power	Advantages	Drawbacks	Cost (Stars)	Popularity (Stars)
Lithium Cobalt Oxide ($LiCoO_2$)	Portable electronics (smartphones, laptops, tablets)	Capacity: 100-200 Wh/kg, Power: 150-200 W/kg	High energy density, stable performance, long cycle life	Prone to overheating, expensive, low thermal stability	*****	****
Lithium Iron Phosphate ($LiFePO_4$)	Electric vehicles, energy storage systems	Capacity: 90-120 Wh/kg, Power: 150-200 W/kg	High durability, less prone to overheating, stable performance	Lower energy density, heavier weight, higher cost	****	****
Lithium Manganese Oxide ($LiMn_2O_4$)	Power tools, electric vehicles	Capacity: 100-150 Wh/kg, Power: 150-200 W/kg	Stable performance, long lifespan	Lower energy density, less thermal stability	****	***
Lithium Nickel Cobalt Aluminium Oxide ($LiNiCoAlO_2$)	Electric vehicles, aerospace	Capacity: 200-250 Wh/kg, Power: 200-300 W/kg	High energy density, high power delivery	Expensive, less durable than other types	*****	***
Lithium Nickel Manganese Cobalt Oxide ($LiNiMnCoO_2$)	Power tools, electric vehicles, energy storage systems	Capacity: 150-200 Wh/kg, Power: 200-250 W/kg	Good balance of performance, cost, and safety	Lower energy density than $LiNiCoAlO_2$, lower lifespan than $LiFePO_4$	****	*****
Lithium Titanate ($Li_4Ti_5O_{12}$)	Buses, large vehicles, energy storage systems	Capacity: 50-80 Wh/kg, Power: 1000-2000 W/kg	Fast charging and discharging, high durability	Lower energy density, higher cost	****	**

Energy Management Systems

As the adoption of distributed energy resources (DERs), such as solar photovoltaic systems, energy storage devices, and electric vehicles, continues to increase, the reliance on energy management systems (EMS) for prosumers has become increasingly important. These systems enable users to schedule their energy consumption, reduce costs, and enhance the reliability and resilience of their energy supply.[13]

Sampling time plays a crucial role in providing the accuracy of data for real-time decision-making, system optimization, and load dispatch. A suitable sampling time ensures that the EMS can react to changing conditions, such as fluctuations in energy generation, consumption patterns, or grid constraints, while balancing the computational and communication requirements of the system.

To provide an overview of the current energy management systems available for prosumers, Table 1.2 presents a summary of a selection of EMS solutions, highlighting their developers, key features, target prosumers, and sampling time ranges.

Table 1.2: Types of EMS

System Name	Developer	Key Features	Target Prosumers	Sampling Time Range
HOMER Grid	HOMER Energy	Microgrid design optimization, load management, renewable integration, cost analysis	Residential, commercial, industrial	1 min - 60 min
EnergyHub	EnergyHub	Demand response, load control, distributed energy resources (DER) integration	Residential, commercial	5 min - 60 min
LO3 Energy Exergy	LO3 Energy	Local energy marketplaces, blockchain-based transactions, peer-to-peer energy trading	Residential, commercial	1 min - 60 min
SolarEdge Energy Manager	SolarEdge Technologies	Solar production monitoring, smart home integration, EV charging control, energy storage optimization	Residential, small commercial	5-minute intervals
OpenEMS	Fraunhofer IEE	Open-source platform, energy storage control, demand-side management, grid services	Residential, commercial, industrial	1 min - 60 min
GreenCom Networks iEMS	GreenCom Networks	Smart home control, demand-side management, energy analytics, renewable integration	Residential, small commercial	1 min - 60 min
Schneider Electric EcoStruxure	Schneider Electric	Building and microgrid management, demand-side management, renewable integration, grid services	Residential, commercial, industrial	1 min - 60 min
Siemens EnergyIP DEMS	Siemens Energy	Distributed energy management, demand response, DER integration, grid services	Residential, commercial, industrial	1 min - 60 min

Current solutions

Fuzzy Clustering Methods (FCM) are commonly implemented to account for the presence of uncertainties in production and consumption. The proposed solutions usually conclude with a sensitivity analysis, indicating potential deviations, tolerances, extreme scenarios, and their associated cost effects. However, these deviations are computed from the same “environment", referring to the set of expressions, model and hypothesis, which most of the time does not provide enough context to rigorously “validate a model.

With the recent developments in Artificial Intelligence and Deep Learning; Reinforcement Learning implementation (Actor-Critic methods) is being proposed for Energy Trading[17], Optimum Scheduling, Internet of Things... The “Depreciation expenditure" in these projects is usually linearized with some “usage rate", and their deviations generally fall within an acceptable tolerance. However, the most critical component involved in energy trading, the Energy Storage System (e.g., Lithium Battery, PtX), exhibits a highly non-linear depreciation behaviour[18]. Even the definition of “depreciation" is a subject of debate - whether it should refer to capacity fade, power fade, or both; which has an effect not only on life expectancy but also on performance[19]. These wrong estimations may have dramatic consequences including negative Return on Investment, profitability, or even question the feasibility of the entire project.

1.3 Problem Formulation

In the realm of solar and wind generation, the best and latest exogenous forecasting *Hybrid Model* has acknowledged success in combining time-series models (historical observations), structural models (meteorological parameters) and *Kalman Filter* to correct the model parameters. However, this succes corresponds to periods day-to-day; the short-term fluctuations have too many degrees of freedom to rely on (wind burst, clouds, etc). When sizing the components and the return of investment, a Cap-ex analysis is usually performed by prosumers based on measured hourly wind and solar resources and consumption; while the energy management system controls the power flow every 15 minutes; and the fluctuations in weather such as clouds or wind bursts may manifest in fractions of a second. Those changes in instantaneous power are out of the reach of Energy Management control and neglected in long-term economic analysis while their effect on battery life may not be negligible. The challenge presented can be formulated as:

- How is the accuracy of the battery's useful lifetime affected by sampling time?
- What sampling time should the Energy Management system use?
- How to verify the battery's cost-effectivenes from an Energy Management system?

1.4 Objectives

This Master Thesis focuses on prosumers in the context of a liberalized electricity market with financial compensation for renewable production as Denmark in 2023. The main goal of developing an EMS can be divided in:

- To take into account the effect of sampling time.
- To pursue the financial interest of the prosumer.
- To design and verify a post-processing algorithm that estimates the progress of battery degradation in function of its performance.
- To design and verify a suitable model that simulates the varying conditions experienced by the battery suitable for degradation analysis.
- To quantify the impact of sampling time on the precision of battery degradation estimation in the model and data.
- To design a suitable EMS that accounts for a cost-efficient system

- To analyze the relationship between cost-efficiency and cost-efficacy
- To develop a simple and effective method to capability EMS.

1.5 Methodology

A prosumer micro-grid will be carefully designed where the necessity of a battery may be questionable. The sizing of the consumption will be profiled as a rural area with the largest household load.

The weather data (wind speed, solar radiance and ambient temperature) is provided by *Photovoltaic Systems Laboratory* with the fastest sampling frame (200ms). This data will be re-sampled to contrast with the desired periods in order to mimic typical weather data provided by public domain.

The impact of EMS in the battery will be analyzed with the help of MATLAB/Simulink. The load profiles will be generated to replicate a common household electrical consumption. Thus, the unique power curve of each appliance is characterized and randomized within time restrictions and seasonal behaviour. A Simulink Model is designed to simulate the power exchange between the battery unit and the load, local generation feeded by weather data and external grid. This simulation results will provide the State-of-Charge profile over time. A post-processing unit is developed in MATLAB to extract the number and depth of the cycles as well as measuring the time that the battery has been idling from the SoC profile. This information will be sorted and processed to compute the *Capacity fade* of the battery as the addition of *cycling aging* and *calendar aging* described by [19].This process will be repeated with different sampling times in order to quantify the relation between accuracy and sampling time.
After selecting the most balanced sampling time between accuracy and computational resources and time an Energy Management System algorithm is designed in Simulink with *Stateflow chart* and its effect in the battery and system's cost-effectiveness is analyzed.

1.6 Scope and Limitations

During the creation of the project, certain aspects were simplified or neglected to ensure the project's focus and scope were maintained. As a result, the following restrictions have been taken into account:

- Power fade of the battery is neglected.
- Temperature of the PV cell is not considered

- Degradation of the generation components is neglected.
- The system's load flow will be represented by active power ($cos(\phi) = 1$) without considering voltage levels.
- The PV system operates only on MPP (maximum power point)

Chapter 2

System Description

Among the various existing hybrid systems, this project focuses on one particular Wind-Solar-Battery hybrid system. This Chapter will provide a detailed overview of the components involved in this hybrid system.

2.1 Prosumer Characterization

Models of the Wind-Solar-Battery hybrid system were developed and validated in [20]. For the purpose of this thesis, these models have been simplified by focusing in load flow. All input variables (*Wind Speed*, *Temperature*, *Solar Irradiance*) and *Load* were provided by the Aalborg University Labaratory.

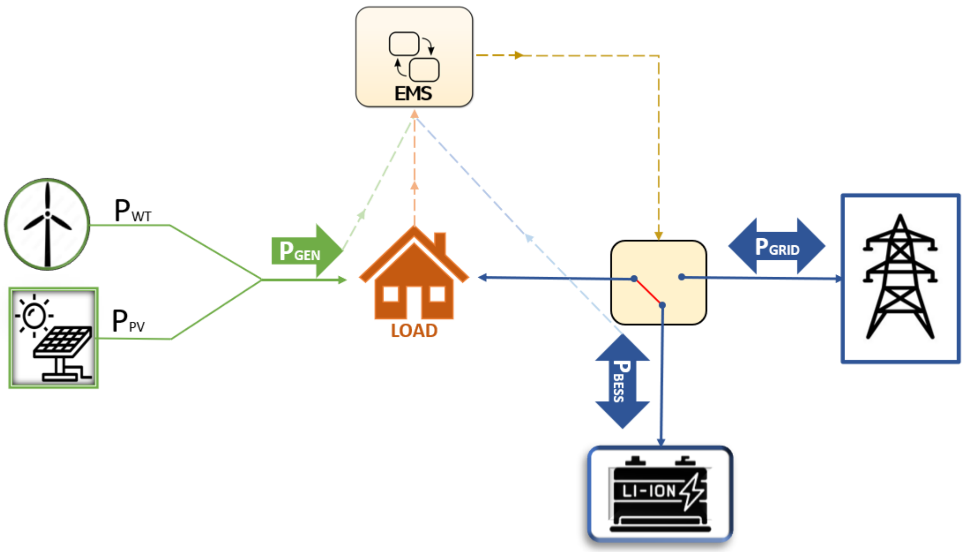

Figure 2.1: Power and Signal Flow of Prosumers Wind-PV-Battery System's Architecture

Table 2.1: Sizes of the components

COMPONENT	MODEL	SPECS
WT	OLW_10kW	15m/10kW
PV	BP Solar BP3220N Module	220W
BESS	[6kW] [6kWh]	[95 RT 0E. . ... ff%]
LOAD	HOUSEHOLD	1 YEAR GENERATED DATA

The Table 2.1 provides brief descriptions of all components utilized in this thesis. The following sections delve into more detailed definitions and performance models.

2.1.1 Wind Turbine Model

A small wind turbine is modeled in Simulink taking into account the *Roughness and height effect*, *Rotor inertia effect* and *Power Curve*

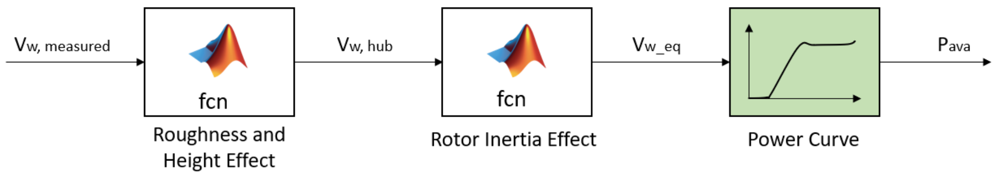

Figure 2.2: Simplified Simulink Model of Wind Turbine

Roughness and Height Effect:

Takes into consideration the difference between the measured wind speed height ($H_{measured}$), the wind turbine hub's height (H_{HUB}) and its environment roughness (z) described in Equation 2.1. For the context of a common prosumer, the environment roughness coefficient is set to 0.25 for rural areas.

$$U_{HUB} = U_{measured} \cdot \frac{ln(\frac{H_{HUB}}{z})}{ln \cdot (\frac{H_{measured}}{z})} \tag{2.1}$$

Rotor Inertia Effect:

The fluctuation of the wind is smothered with the inertia provided by the rotors weight. Authors in [20] validated the implementation of a first-order low-pass-filter as equivalent of this smoothing effect of *natural constant* $\tau_{v\omega}$ computed from the Expression 2.2 and discretized using *Backward-Euler Method*.

$$\tau_{v\omega} = \frac{\omega_{rated} * J}{3 \cdot T_{rated}} \cdot \frac{U_{rated}}{U_{HUB}} \tag{2.2}$$

Power Curve:

The power curve used in the model is a look-up table of the model OLW-10kW provided by the manufacturers.

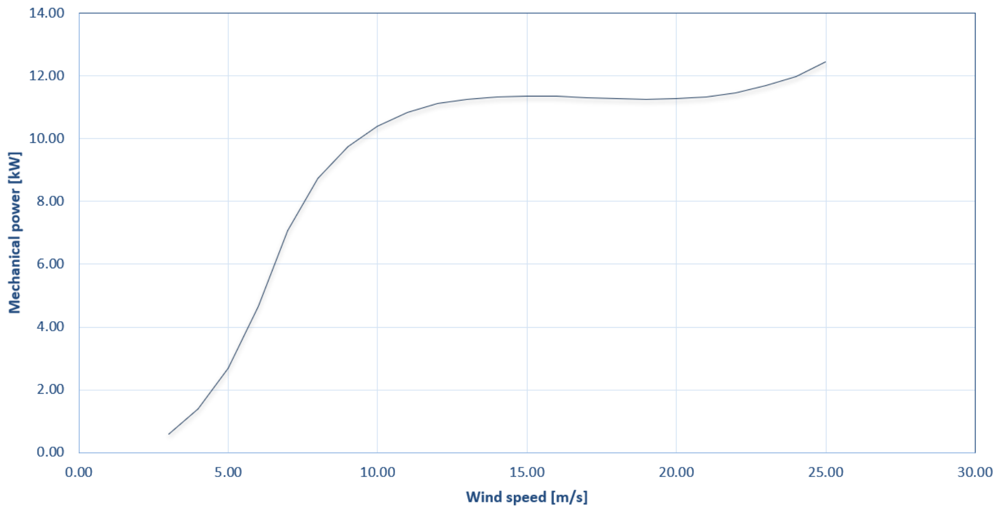

Figure 2.3: OLW-10kW Power Curve Provided by the Manufacturers [21]

2.1.2 Solar Photovoltaic System

The Photovoltaic system (PV) has been modeled in Simulink. This model incorporates the *area effect*, which smothers the output signal according to the size of the solar panel area acting as a *low-pass-filter*. The power has been modelled with the 'Sandia Model' [22], which predicts power output under maximum power point tracking (MPPT) conditions for each individual solar cell. The pa is composed of total installed power of $6kW_p$.

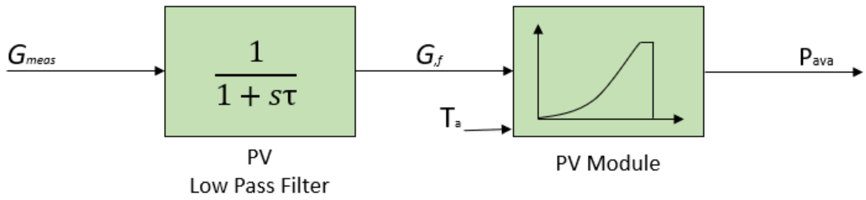

Figure 2.4: Simplified Simulink Model of PV

2.1.3 Battery Energy Storage System

A energy storage system is modeled with mathematical expressions to compute the SoC over time taking into account the *Round trip efficiency* following the proposition from [20].

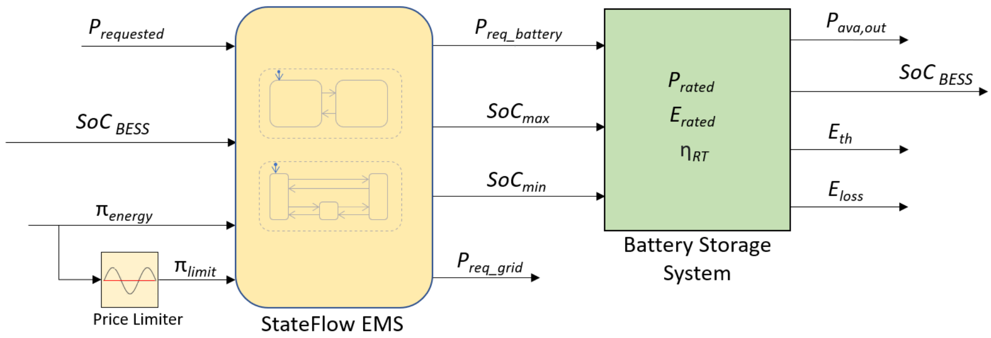

Figure 2.5: Simplified Simulink Model of Battery Energy Storage System with StateFlow EMS

Battery model parameters

The storage model has been parameterized by:

- P_{rated} : Maximum symmetric charging / discharging power in kW.
- E_{rated} : Maximum energy storage capacity in Kwh.
- ϵ_{RT}: Round trip efficiency.
- $P_{requested}$: Power required to balance the micro-grid (demand positive / generation negative) in kW.

- $P_{req\_Battery}$: Power requested to the battery by the *Battery Management System* in kW.
- P_{ava_out}: Power supplied by the battery (discharge positive / charge negative) in kW.
- SoC_{BESS}: State of the charge.

SoC estimation

The estimation of the State-Of-Charge of the battery has been computed with the *Cuolomb Counting Method* validated from [23].

2.1.4 Battery Management System

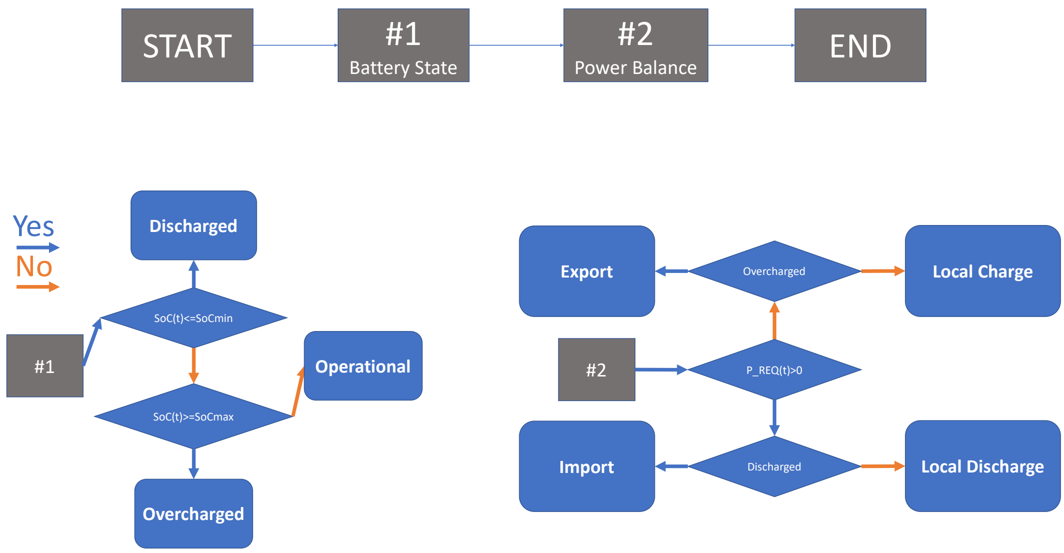

Figure 2.6: Stages of Battery Management System

In the previous flowchart Figure 2.6 the basic energy management system algorithm is depicted in two stages:

- Battery State: In the first stage the current State of Charge is compared with upper and lower limits to define its state as *Discharged*, *Operational* or *Overcharged*.
- Power Balance: In the second stage the sign of the power signal and the state of the battery define four operational actions: *Export*, *Import*, *Local Charge*, or *Local Discharge*.

The details of each state are defined in the following set of expressions:

- Start: Initialize the input variables:

$$P_{LOAD}(t); P_{GEN}(t)); SoC(t) \tag{2.3}$$

- And the parameters:

$$P_{charge\_max} == P_{discharge\_max} = P_{bat\_max} \tag{2.4}$$

- Battery State:

$$BatteryState = f(SoC(t)) \tag{2.5}$$

- Power Balance:

$$P_{BAL}(t) = P_{GEN}(t) - P_{LOAD}(t) + P_{BAT}(t) + P_{GRID}(t) = 0 \tag{2.6}$$

$$P_{REQ} = P_{LOAD}(t) - P_{GEN}(t) = P_{BAT}(t) + P_{GRID}(t) \tag{2.7}$$

And finally, the resulting action states :

- Import & Export:

$$P_{BAT}(t) = 0; P_{GRID}(t) = P_{REQ}(t) \tag{2.8}$$

- Local Charge:

$$P_{BAT}(t) = max\{P_{REQ}(t), -P_{bat\_max}\} \tag{2.9}$$

$$P_{GRID}(t) = min\{0, P_{bat\_max} + P_{REQ}(t)\} \tag{2.10}$$

- Local Discharge:

$$P_{BAT}(t) = min\{P_{REQ}(t), P_{bat\_max}\} \tag{2.11}$$

$$P_{GRID}(t) = max\{0, P_{REQ}(t) - P_{bat\_max}\} \tag{2.12}$$

2.1.5 Prosumers Load

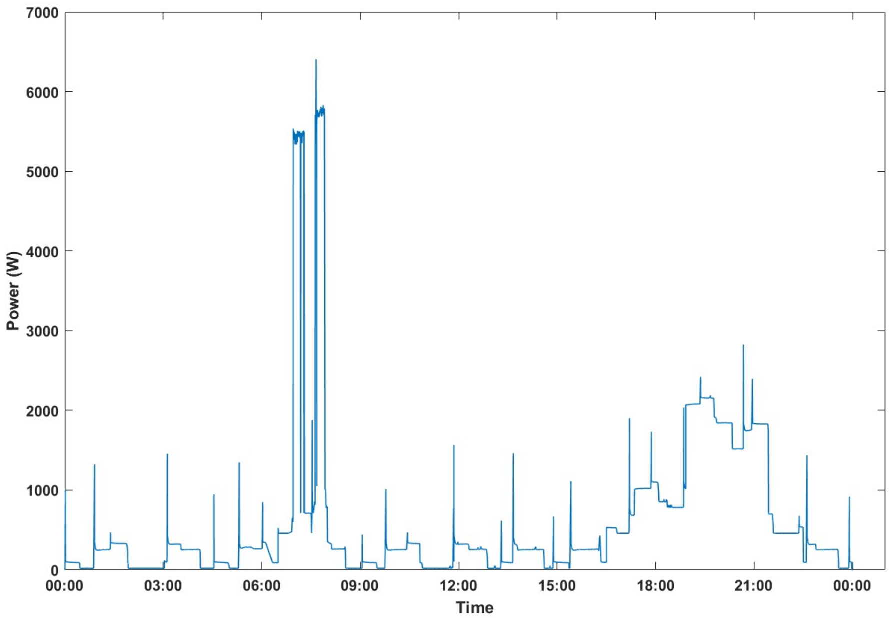

Figure 2.7: Prosumers Load in one day during winter

Figure 2.7 depicts a high-resolution household load, generated based on a probabilistic distribution reflecting the realistic load profiles and usage patterns of every appliance distinguishing weekdays and weekends as well as seasonal behaviour according to Cluster 4 in [24].

2.2 Post-Processing Block

In this project the degradation of the battery (remaining useful lifetime) is defined as capacity fade due to *Cycle aging* and *Calendar aging* computed into a *MATLAB function box* which parameters are introduced and validated in [19]:

- Cycle aging is the capacity fade due to depth of discharge and number of cycles. Is computed by the equation 2.13 where *cd*, *nc* and *SoC_av* represent the depth of discharge, number of cycles in that level and average state of charge in that cycle respectively.

$$Cf_{cyc} = 0.021 \cdot e^{-0.1943 \cdot SoC\_av} \cdot cd^{0.7162} \cdot nc^{0.5} \tag{2.13}$$

- Calendar aging is the capacity fade due to idle. It is depicted in expression 2.14 where SoC_l and t represent the energy level and time in months the storage system is idling, respectively.

$$Cf_{cal} = 0.1723 \cdot e^{0.007388 \cdot SoC\_l} \cdot t^{0.8} \tag{2.14}$$

In order to compute Cf_{cyc} in the expression 2.13, the SoC profile is simulated for one year with the highest resolution and replicated. The cycles are extracted using *Rainflow residue processing algorithm for fatigue damage estimation* [25], sorted by depth of discharge and energy level in bins of 5% and counted. Parallelly, another algorithm collects and sorts the idling time and storage level for Equation 2.14.

2.3 Scenarios and Study Cases

The behaviour of the battery degradation is simulated and processed under different scenarios as architecture configurations and two cost-benefit cases with and without taking into account battery degradation and deviation.

Scenario A: Wind-PV-Battery

Scenario B: Wind-Battery

Scenario C: PV-Battery

Chapter 3

Simulation Results

Other authors [] computed the End-of-Life Time (80% initial Capacity criteria) as the time that takes to reach 20% of Degradation. However, this time is computed modelling one year and assuming a linear progress the following years. Figure [] exhibits the difference between linearizating one year or replicating the same cycles through six following years (364 weeks). Nevertheless, replication of cycles is not accurate either since the repeating of same cycles in the battery prevents significantly the degradation. In realistic modelling of 7 years those following cycles would be with different depth of charge and their corresponding degradation would be higher.

3.1 Effect on sampling time

As introduced in Section 2.3 three different scenarios are analysed and compared. Each of these scenarios represents a different architecture of the power system, highlighting the variations in design and potential outcomes.

3.1.1 Scenario A: Wind-PV-Battery

In this scenario different sampling times are implemented is the simulation of an architecture of wind turbine [10kW], solar panel [6kW], characterized household load and storage system [6kW].

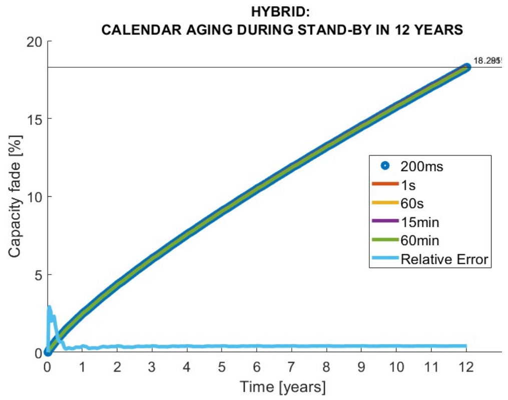

Figure 3.1: SCENARIO 1 - Cycling fade

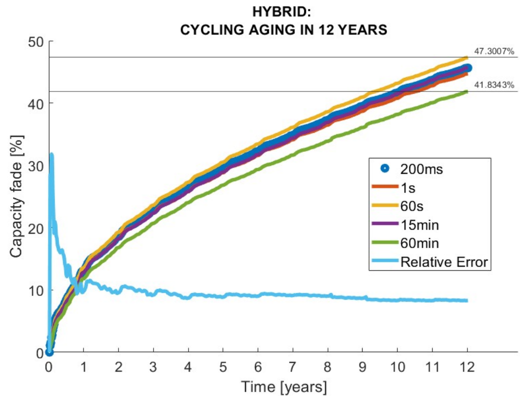

Figure 3.2: SCENARIO 1 - Idling fade

3.1.2 Scenario B: Wind-Battery

The second scenario stands for the architecture with only wind turbine.

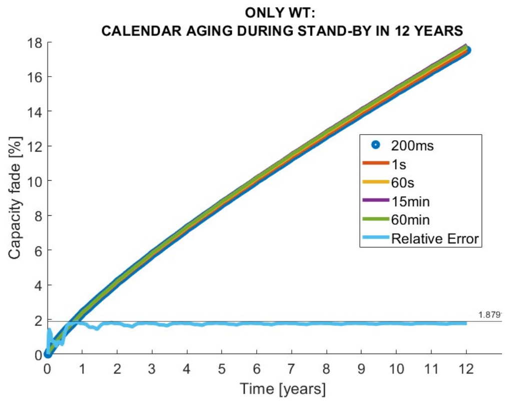

Figure 3.3: SCENARIO 2 - Cycling fade

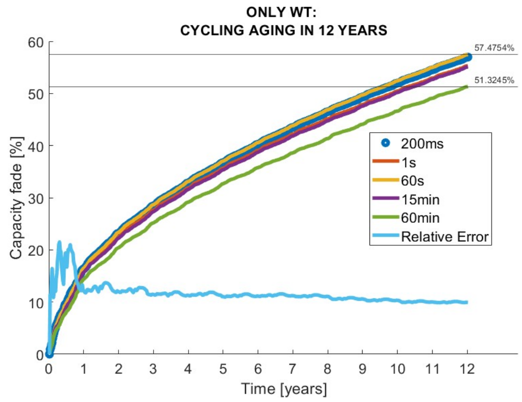

Figure 3.4: SCENARIO 2 - Idling fade

3.1.3 Scenario C: PV-Battery

The third scenario stands for the architecture with only PV.

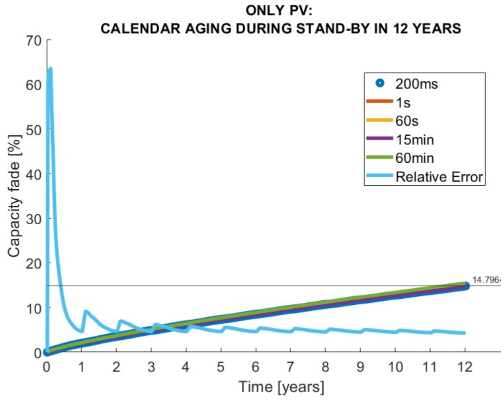

Figure 3.5: SCENARIO 3, Cycling fade

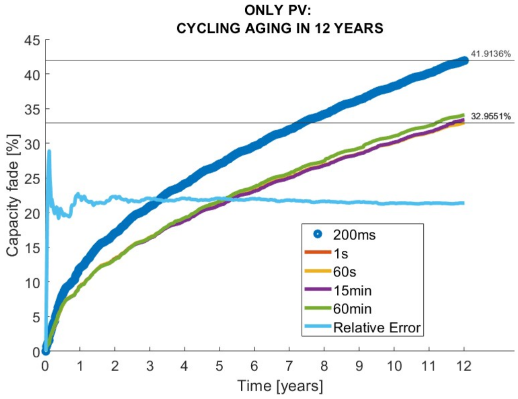

Figure 3.6: SCENARIO 3, Idling fade

The previous section drives the following possible conclusions:

- The calendar error rate is negligible. The micro-idling periods are randomly enhanced and diminished cancelling each other.
- The cycling error has the highest fluctuations. The 1-second resolution signal is indistinguishable from the highest 200 ms. However, the rest of them differs in different scenarios.
- Wind and solar have different effects on the error rate. In order to explore this relation further scenarios have been simulated with different wind-solar integration.

3.1.4 Summary of results

Figure 3.7 exposes the variation of maximum error rates when computing cycle degradation in different sampling times. The horizontal axis represents wind integration as multiples of the initial 10kW while the vertical axis represents solar integration as multiples of 6kW. The color bar represents the corresponding error rate in % as the maximum error found following procedures from previous section.

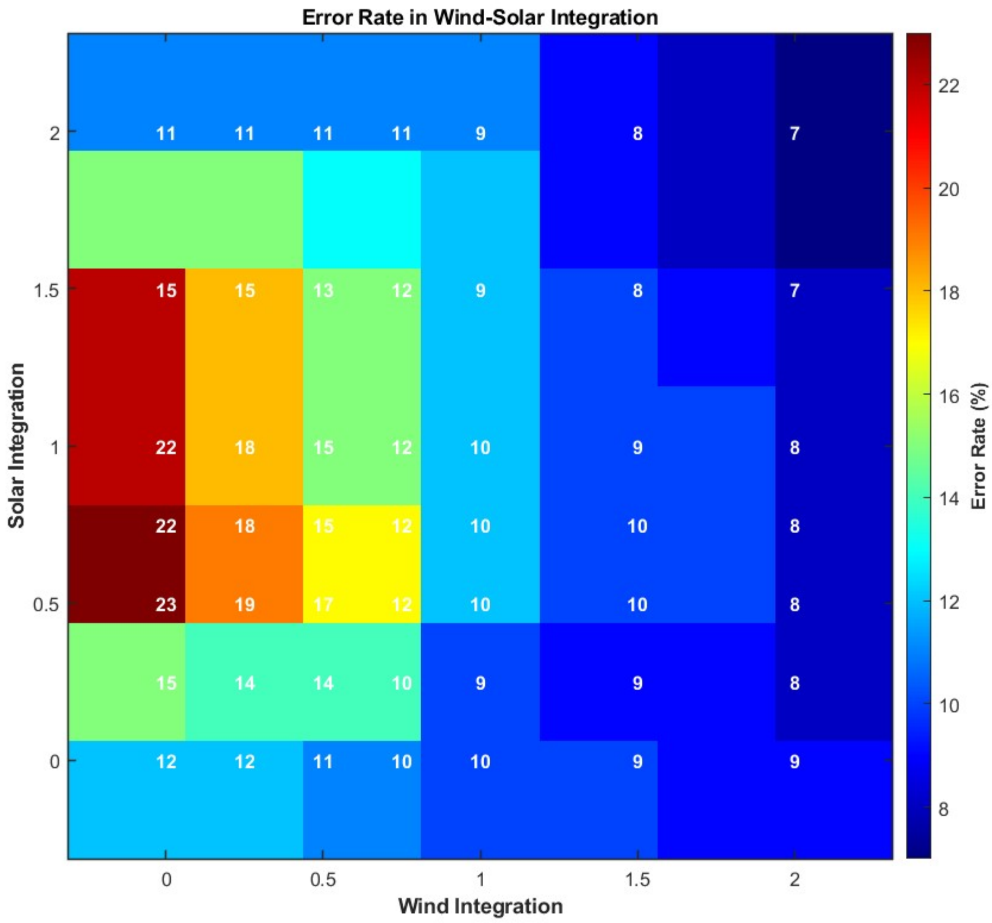

Figure 3.7: Error rate in different integration scenarios

As suspected, solar production includes more high-frequency variations that may affect the battery's life-time. The previous map Figure 3.7 suggests that the more solar panel power we add to the installation, the more high frequency fluctuations we miss, and therefore higher error rate between cycling degradation in different sampling times. Over some limit, in this case 150% of initial installed power, the production becomes saturated and the error rate decreases.

3.1.5 Further Analysis

As outlined in Subsections 2.1.1 and 2.1.2 the modelling on the Wind Turbine and Solar panels, the implementation of the *Rotor inertia effect* and *Spacial smoothing* *effect* have some similarities. In fact, both act as low-pass filters to weather fluctuations.

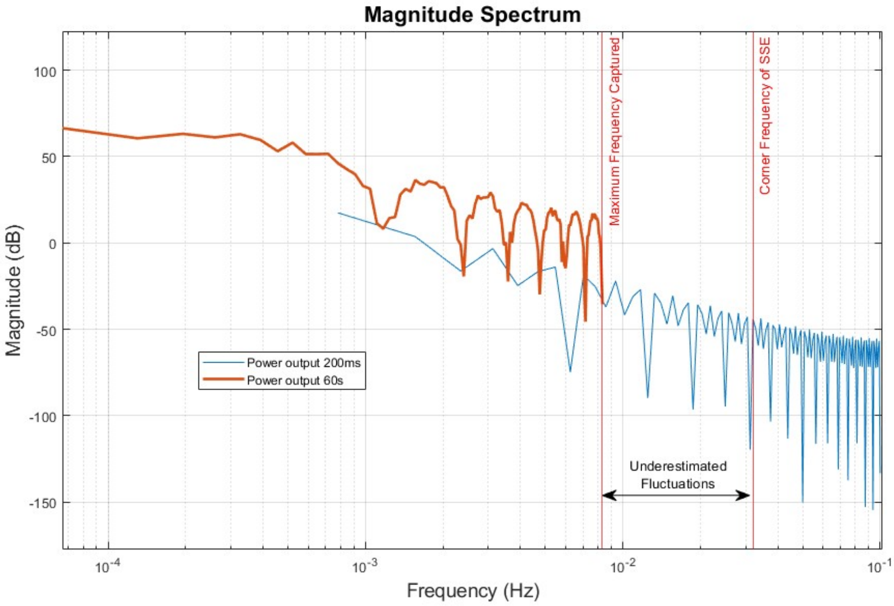

Figure 3.8: Rotor inertia effect vs Spacial smoothing effect

Therefore, all energy exchange in the frequency band acting between the sampling time and the corner frequency of the solar panel's area-smooth effect, and their corresponding cycles information will be lost.

Chapter 4

Assesment Studies

In this chapter, two different optimization methods are characterized. First, Section 4.1 represents an explotative iterative method where some parameters are tuned until finding the best point of minimum cost or maximum profit. However, battery degradation is not considered in the procedure. Second, Section 4.2 represents another candidate solution from a much more powerful tool (e.g. RL trained bot) which counts with forecasts, consumption patterns, and estimates within confidence levels. Ideally, this agent could estimate the cost of the next cycle and decide whether it will be profitable or not.

4.1 Test Case A

There are many approaches to developing an Energy Management System (EMS). In this project, the EMS presented in the subsequent section represents a basic approach created using StateFlow in MATLAB. Notably, this model was made for the singular priority of cost reduction, not having a trade-off with battery degradation.

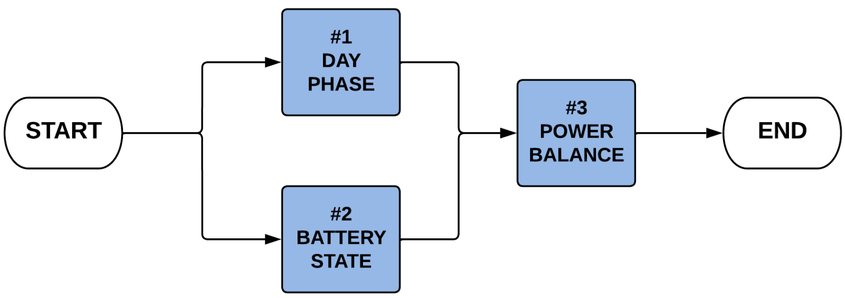

Figure 4.1: Energy Management System's stages

As mentioned in the Section 2.1.4 the energy management system is represented in two stages: *Battery State* and *Power Balance*. However, the approach taken introduces an additional stage that operates in parallel with the battery state, *Day Phase*. Day phase is a decision maker of whether energy should be imported or exported.

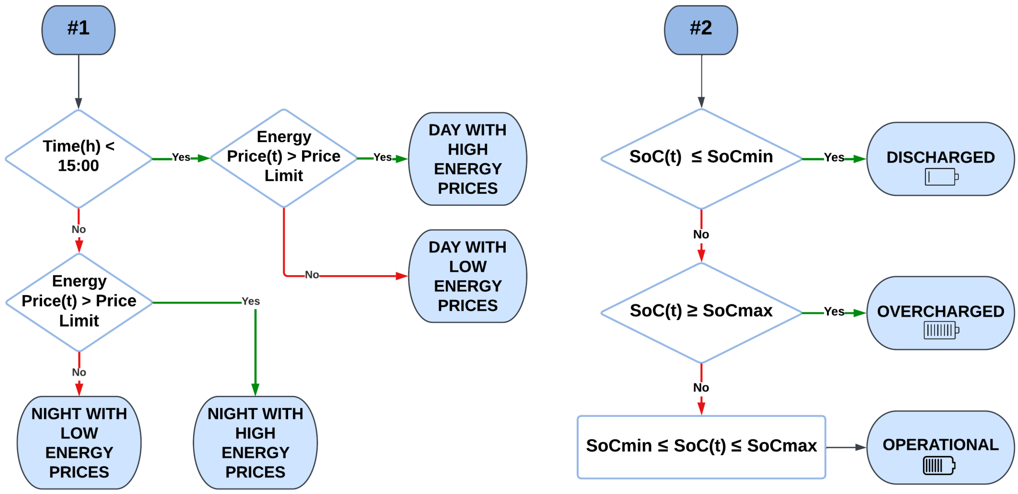

Figure 4.2: Day Phase and Battery State

Referring to the grantt chart in Figure 4.2, it is evident that the Day Phase results in four different outcomes. These outcomes vary based on the time of day, categorized as either <15:00 representing day or >15:00 representing night with the energy price at that moment. For a clearer perspective, decisions made throughout a single day are illustrated in Figure 4.3. This figure highlights that the price limit is determined daily, based on the average import energy price and is dividing the day on either high or low energy prices.

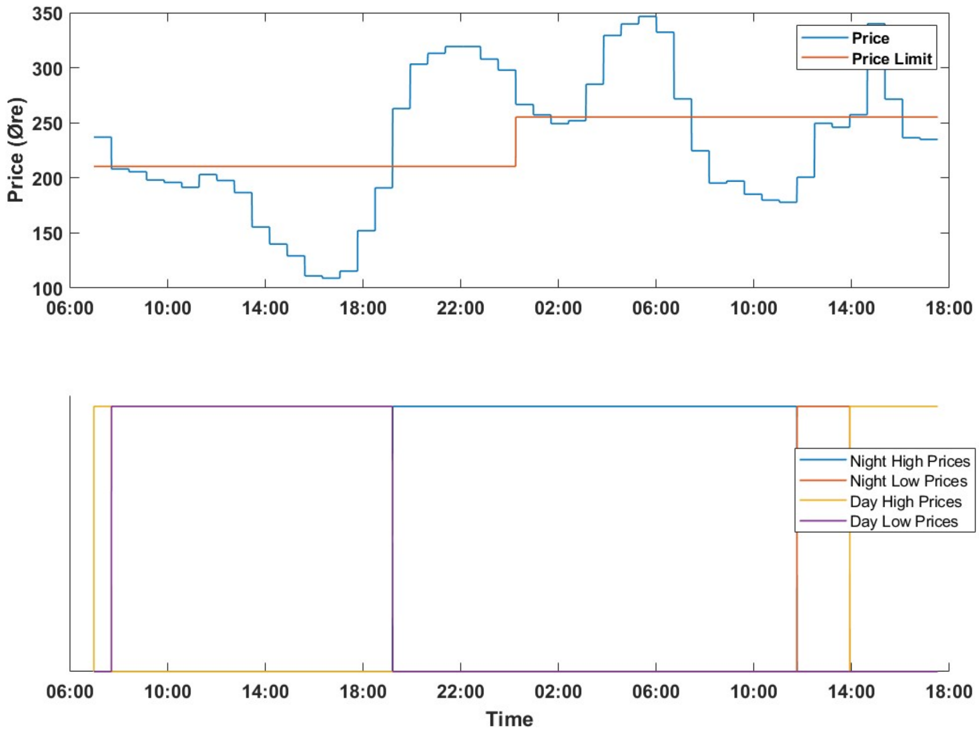

Figure 4.3: *Figure A:* Price and Set Price Limit; *Figure B:* Day Phase Decision

The "Power Balance" stage, depicted in Figure 4.4 and detailed in Section 2.1.4, outlines the operational framework of the developed EMS. The system is designed to consistently maintain power balance. This is achieved by integrating power requested with two prior stages, resulting in five specific outcomes, all of which are detailed in Section 2.1.4. For a visual representation of the EMS operation and its decision-making processes, refer to the grantt chart represented in the Figure 4.4.

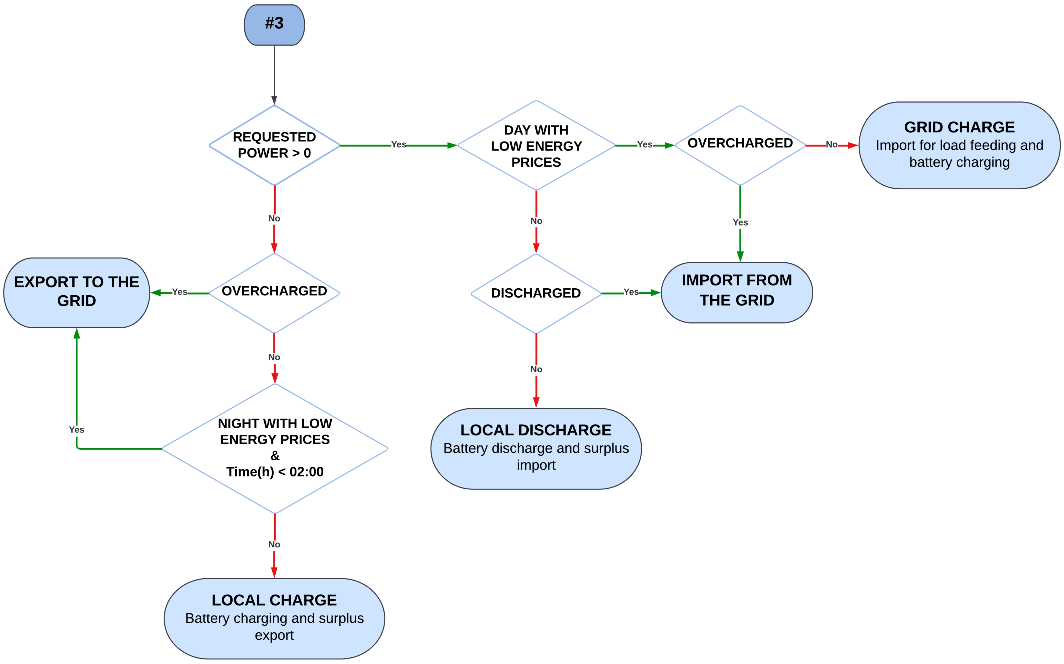

Figure 4.4: Power Balance of the Energy Management System

The developed EMS with the SoC 0-100% has been optimized for cost reduction, resulting in a total accumulated cost of around 2000 kr over one year shown in the Figure 4.5. However, an analysis of battery degradation under this system shows a significant reduction in battery lifespan, with the battery reaching its end-of-life in just 6 years shown in the Figure 4.6.

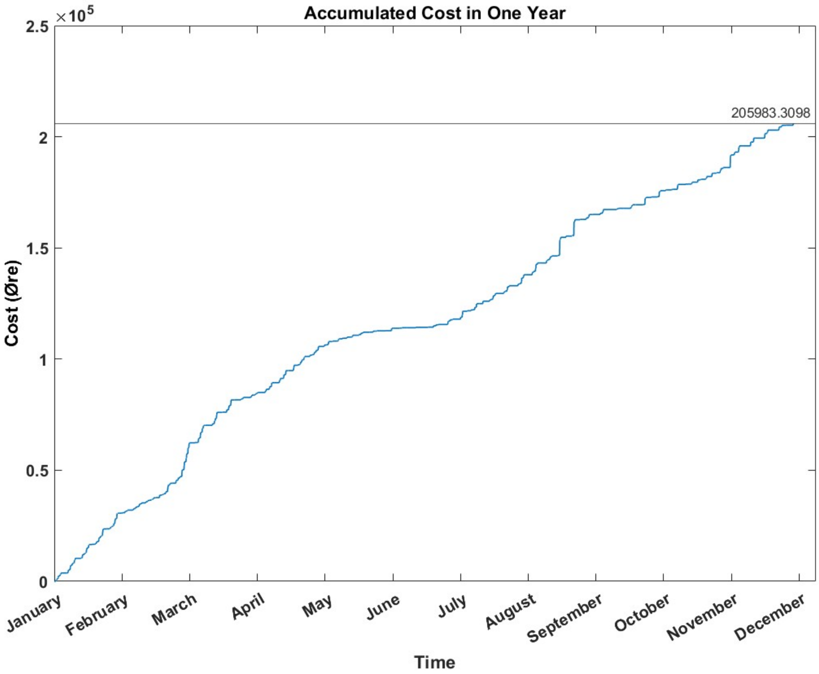

Figure 4.5: Accumulated Energy Cost in One Year Using Developed EMS

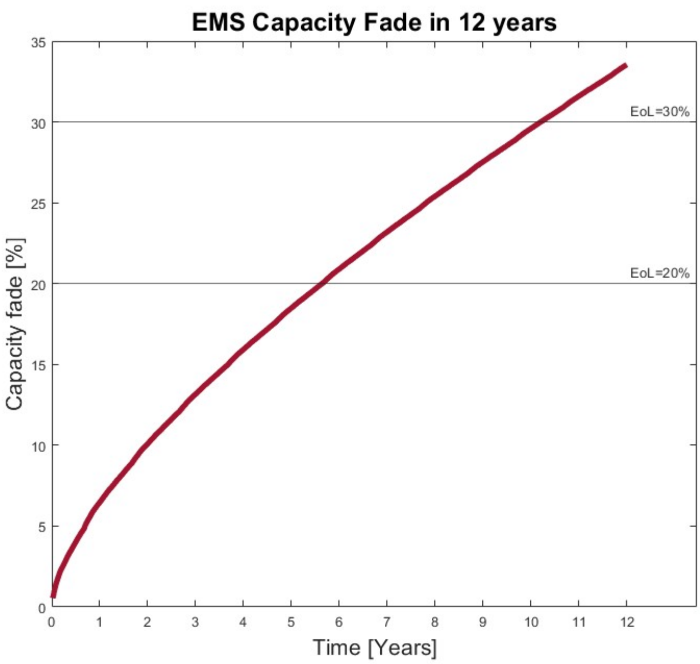

Figure 4.6: Capacity fade under EMS conditions

This data indicates that while the EMS effectively minimizes costs, it does so by compromising battery longevity. The shortened operational life of the battery could lead to increased replacement costs. Therefore, the current EMS approach is not optimal due to its inability to balance cost efficiency with battery lifespan considerations.

4.2 Test Case B

When optimizing the EMS performance, one problem arrives: Either we count for the non-linear behaviour, limiting the number of iterations or we linearize the problem to reduce its computational requirements. Most of the authors opt for the second option since it allows them to explore all the latest machine learning and optimisation tools. In contrast, in proper optimization statements [26] the algorithm seems undeniably effective. “If the cost of using the battery for the next cycle compensates the outcome, is profitable”. However, that represents the very well-known dilemma of “marginal cost vs average cost". The cost of the next cycle is equivalent to the marginal price of using the battery must be compared with the cost of the energy, taking into account forecasting, available energy and consumption patterns. However, since the "cost" of using the battery is highly non-linear, the depreciation (capacity fade) corresponding to the first cycles is the highest. Using that marginal cost would be an error, since the algorithm may fall into a local minimum by not using the battery at all or the opposite case, when using the battery is not cost-effective over its lifetime but the following cycles are relatively affordable. Figure 4.8 display the Marginal curve of the energy used by the battery during its lifetime.

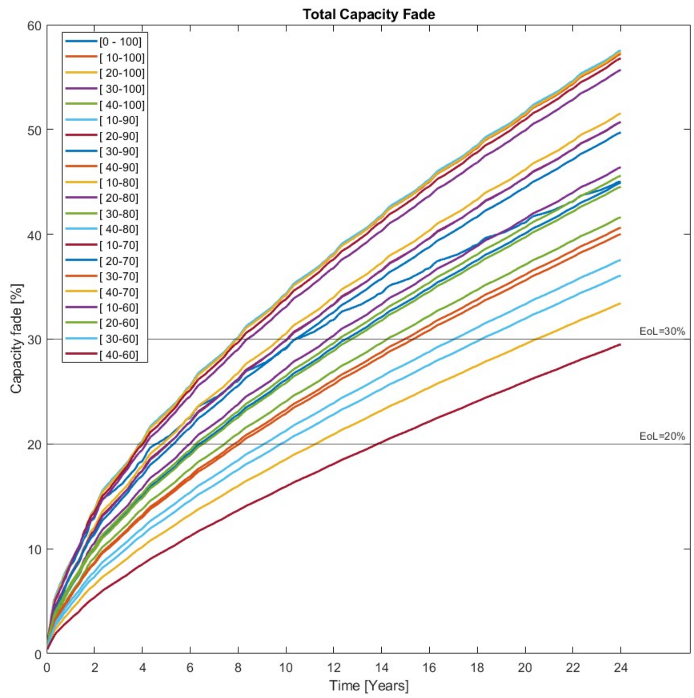

Figure 4.7: Capacity fade for 25 cases

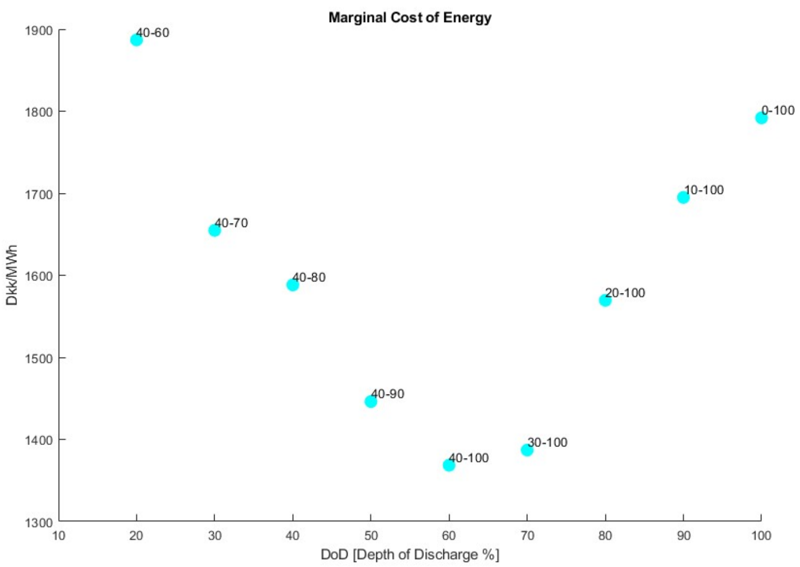

Figure 4.8: Marginal Cost of Energy

4.3 Proposed Method

In this section, we investigate the possible incoherence and we propose a method to overcome them. In order the find the optimum point, the candidate points are extracted from a Pareto chart:

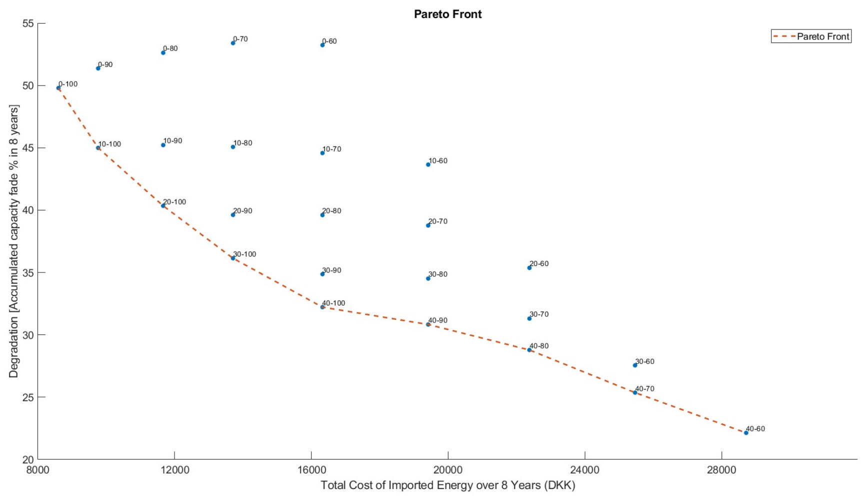

Figure 4.9: Pareto chart

Marginal cost does not represent average cost, thus the minimum point 40-100% from Figure 4.9 represents the highest efficiency in battery discharge, but not the best cost-effective option from the user's point of view. Combining the average cost with the expense of a new battery acquisition (from lifetime results) a new distribution is found in Figure 4.10.

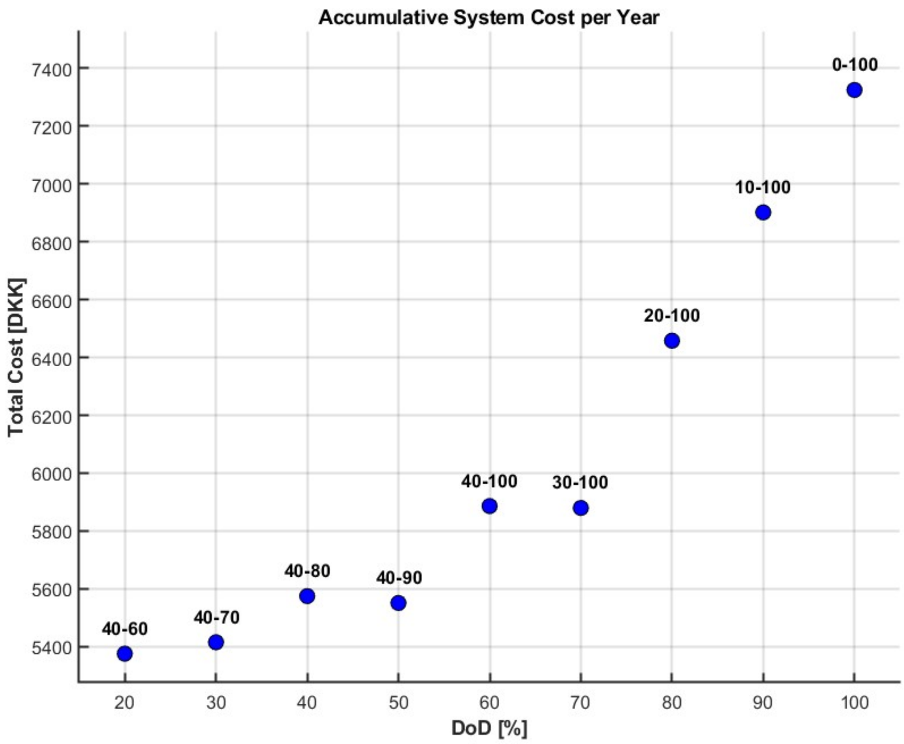

Figure 4.10: System's effective cost per year

As was expected, in an installation where the battery inclusion was questionable, the more we use the battery (augmenting it's limits on the depth of discharge) the less profit we achieve from it. However, this solution can not be found in any iterative process or marginal cost computation.

Chapter 5

Comparison & Conclusion

Section 4.1 represents an optimized cost function with the best solution found at 2060 DKK in energy imported per year and 6 years of the battery's expected lifetime. However, its effective cost, taking into account battery acquisition cost, would be 6225 DKK, 24% higher than that of the simpler Pareto-lifetime method proposed in Section 4.2.

Table 5.1: Results comparison

METHOD	Cost of Imported Energy [DKK]	Battey's Lifetime [years]	Effective yearly cost [DKK]
Iterative Optimization	2060	6	6225
Marginal Cost	2240	6.5	6085
Pareto	3590	14	5035

Table 5.1 highlights the importance of a validated method to compare the cost-effectiveness of any given Energy Management System or Battery Management System and suggests considering that:

- Pre-analysis of the installation's profitability is critical.
- The non-linear effect of the battery's depreciation is predominant in economic analysis,
- The "Marginal Cost vs Average Cost" analysis may be much more capable than single decision-based algorithms at pursuing users economic interest.
- Any EMS / BESS algorithm candidate should be contrasted with a simple and validated economic analysis.
- The "Pareto-Front with Battery Acquisition Cost" method may serve as validation method.

5.1 Future Work

This Master Thesis project has focused on providing a base work frame for the upraising research into the battery optimization field. It aimed to achieve the largest and most solid impact in the current State-of-Art, given its time, workforce and resources. The tasks that were not within this project's scope, but would provide an excellent opportunity to enhance this work, are listed below:

- Some key cases were analysed in the relationship between solar integration and sampling time. However, they were all considered in the same household profile. Different load sizes and patterns (farm, industry, neighbourhood) could provide interesting results.

- Power fade has not been taken into account, since manufacturers use capacity fade to define their warranty. However, its effect, within a voltage and current simulated environment may give a more technical and detailed point of view.

- Figure 3.8 quantifies the frequency gap of lost information, which indicated that the amount of energy and its power profile contained in that frequency band may be estimated by characterizing solar radiance fluctuations with distribution parameters as *variance* (normal distribution - white noise), *scale* (Weibull distribution), *skewness*, *kurtosis*...etc.

- Histogram in Figure5.1 identifies exactly the cycles that are being lost in high frequency fluctuations. The estimation of those cycles is another workaround to be able to work within larger sampling times.

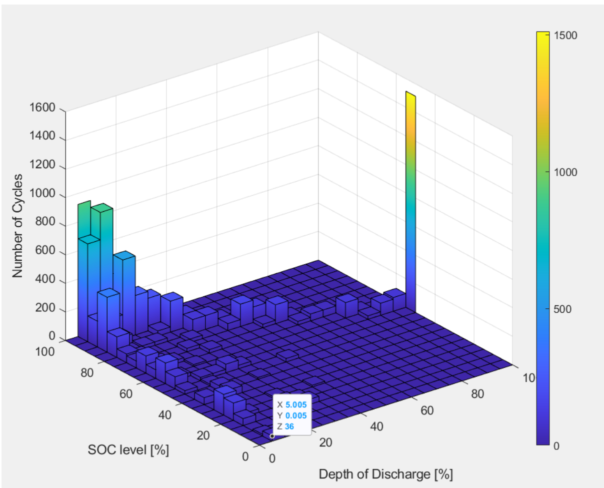

Figure 5.1: Histogram of Battery Cycles

Bibliography

[1] *Climate change in 2050: the implications of a heating world*. URL: https://www.fidelity.com.sg/beginners/esg-investing/climate-change-in-2050.

[2] *The climate crisis: the causes, the effects and the solutions*. URL: https://www.enelgreenpower.com/learning-hub/energy-transition/climate-change-causes-consequences.

[3] United Nations. *Climate Action*. URL: https://www.un.org/en/climatechange/science/causes-effects-climate-change.

[4] International Renewable Energy Agency. *World Energy Transitions Outlook 2023: 1.5°C Pathway*. 2023. ISBN: 9789292605278. URL: www.irena.org.

[5] *Statista*. URL: https://www.statista.com/.

[6] "Average monthly electricity wholesale price in Denmark from January 2019 to January 2023". In: *Statista* (). URL: https://www.statista.com/statistics/1271525/denmark-monthly-wholesale-electricity-price/.

[7] *Deloitte Resources 2020 Study*. Tech. rep.

[8] *Battery Pack Prices Cited Below $100/kWh for the First Time in 2020, While Market Average Sits at $137/kWh*. URL: https://about.bnef.com/blog/battery-pack-prices-cited-below-100-kwh-for-the-first-time-in-2020-while-market-average-sits-at-137-kwh/.

[9] International Renewable Energy Agency. *RENEWABLE ENERGY STATISTICS 2021 STATISTIQUES D'ÉNERGIE RENOUVELABLE 2021 ESTADÍSTICAS DE ENERGÍA RENOVABLE 2021 About IRENA*. 2021. ISBN: 978-92-9260-356-4. URL: www.irena.org.

[10] Caio Cesar Moreira Chagas et al. *From megawatts to kilowatts: A review of small wind turbine applications, lessons from the US to Brazil*. Apr. 2020. DOI: 10.3390/su12072760.

[11] Layla Sawyer. *Design: Think Things Studio Barcelona CEC = Citizen Energy Community DER = Distributed Energy Resource DSO = Distribution System Operator EV = Electric Vehicle GO = Guarantee of Origin PPA = Power Purchase Agreement PV = Photovoltaic REC = Renewable Energy Community TSO = Transmission System Operator*. Tech. rep.

[12] *Evolution of solar PV module cost by data source, 1970-2020*. URL: `https://www.iea.org/data-and-statistics/charts/evolution-of-solar-pv-module-cost-by-data-source-1970-2020`.

[13] Lee Wai Chong et al. *Hybrid energy storage systems and control strategies for stand-alone renewable energy power systems*. Dec. 2016. DOI: `10.1016/j.rser.2016.07.059`.

[14] Arne Surmann et al. "Empowering Consumers within Energy Communities to Acquire PV Assets through Self-Consumption". In: *Electricity* 3.1 (Feb. 2022), pp. 108–130. DOI: `10.3390/electricity3010007`.

[15] Md Monirul Islam, Cihan H. Dagli, and Zeyi Sun. "A model to estimate the lifetime of BESS for the prosumer community of manufacturers with OGS". In: *Procedia Computer Science*. Vol. 168. Elsevier B.V., 2020, pp. 186–194. DOI: `10.1016/j.procs.2020.02.274`.

[16] Eea. *Energy prosumers in Europe - Citizen participation in the energy transition*. Tech. rep.

[17] Amanda Jayanetti, Saman Halgamuge, and Rajkumar Buyya. "Deep reinforcement learning for energy and time optimized scheduling of precedence-constrained tasks in edge–cloud computing environments". In: *Future Generation Computer Systems* 137 (Dec. 2022), pp. 14–30. ISSN: 0167739X. DOI: `10.1016/j.future.2022.06.012`.

[18] Daniel Ioan Stroe et al. "Operation of a grid-connected lithium-ion battery energy storage system for primary frequency regulation: A battery lifetime perspective". In: *IEEE Transactions on Industry Applications* 53.1 (Jan. 2017), pp. 430–438. ISSN: 00939994. DOI: `10.1109/TIA.2016.2616319`.

[19] Daniel-Ioan Stroe et al. *Accelerated Lifetime Testing Methodology for Lifetime Estimation of Lithium-ion Batteries used in Augmented Wind Power Plants*. Tech. rep.

[20] Lennart Petersen et al. "Validating performance models for hybrid power plant control assessment". In: *Energies* 12.22 (Nov. 2019). ISSN: 19961073. DOI: `10.3390/en12224330`.

[21] *Olsen Wings*. URL: `https://olsenwings.dk/olw-products/`.

[22] *pvpmc.sandia.gov*.

[23] Alejandro Gismero, Erik Schaltz, and Daniel Ioan Stroe. “Recursive state of charge and state of health estimation method for lithium-ion batteries based on coulomb counting and open circuit voltage”. In: *Energies* 13.7 (Apr. 2020). ISSN: 19961073. DOI: 10.3390/en13071811.

[24] Gianluca Trotta. “An empirical analysis of domestic electricity load profiles: Who consumes how much and when?” In: *Applied Energy* 275 (Oct. 2020). ISSN: 03062619. DOI: 10.1016/j.apenergy.2020.115399.

[25] C. H. McInnes and P. A. Meehan. “Equivalence of four-point and three-point rainflow cycle counting algorithms”. In: *International Journal of Fatigue* 30.3 (Mar. 2008), pp. 547–559. ISSN: 01421123. DOI: 10.1016/j.ijfatigue.2007.03.006.

[26] Levente Tamas Toth & Shraddha Maslekar. *Energy Management for Household Prosumer*. Tech. rep.