Energy Management for Household Prosumer

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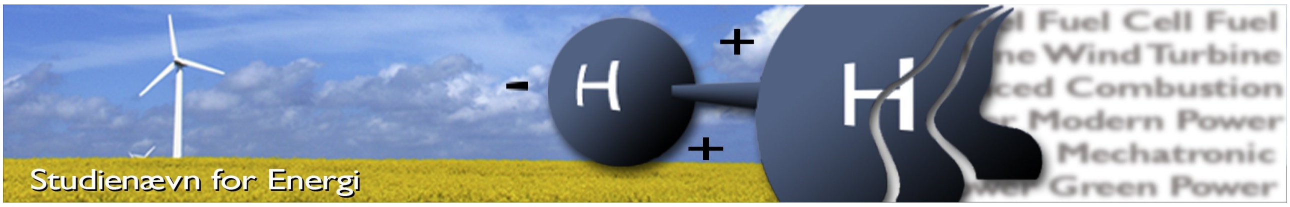
STUDENT REPORT



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Synopsis

This Thesis proposed an effective optimization based energy management algorithm for household prosumers with various assets like: photovoltaics, battery, heat pump or electric vehicle (EV). The selected optimization technique was Dynamic Programming. The developed algorithm was effective in utility bill minimization by scheduling the prosumers battery and EV charging. It has accounted for dynamic electricity prices, battery degradation, user comfort and weather forecast. The system's economical benefits has been verified with a long term financial analysis which proved its ability of significant cost savings. The effect of short term forecast and two different dispatch strategies were also tested. Its feasibility was validated in a simulation environment as well as in a laboratory setup.

Preface

Energy Engineering must provide solutions for future renewable transmission. They have to take into account small scale production and cover the low voltage side as well. Supporting consumers and distribution system operators with innovative and practical methods in their green aspirations is essential for success.

Thus, this thesis proposes a modern solution for household energy management, based on optimization techniques. Prosumers and their powerflow and energy management systems are becoming a highly covered and researched area in modern engineering. The author's goal was to develop an effective system that is flexible enough to incorporate various assets which could be part of any future prosumers home. Furthermore, the main goal of minimizing the energy bill has to be achieved in such a manner that it brings benefits not only for the prosumer but also the local distribution network.

Reader's Guide

This Thesis was written based on information extracted from literature, reports, data sheets and web pages as well as the authors own works. The sources are cited through the whole report and can be found in the Bibliography. The references have been cited with the IEEE citation style, i.e. [number] is referring to the source. Furthermore, figures, tables and equations are labeled according to the number of the corresponding chapter and can be found in the List of Figures and List of Tables. Figures and graphs which lack reference have been created by the authors with softwares like Matlab, Microsoft Visio or Smartdraw. The thesis has been handed in a digital version (PDF).

Abstract

As the share of renewable energy sources are increasing in the electricity production, it became affordable for households to set up their own green production and become prosumers. Governmental incentives are also encouraging this trend through feed in tariffs or reduced taxes. Nowadays, prosumers could include numerous devices in their set up such as: photovoltaic panels, batteries, small wind turbines, heat pumps, etc. The motivation behind these systems is mainly to gain financial benefits on the reduced energy bills but also to aid the fight against climate change. However, because of the volatile nature of renewables, it is important to also invest in a compact energy management system (EMS), which governs all the power flows of the prosumer in an effective manner.

These systems utilize sophisticated optimization algorithms to schedule the prosumers battery or Elecric Vehicle (EV) charging. This thesis aims to develop an EMS which is capable of scheduling the power dispatches of the prosumer's devices, while achieving electricity bill minimization, providing user comfort and constraining the maximum power drawn from the grid. A flexible solution which can be implemented at a wide range of prosumers with different set ups. It requires long term analysis to ensure financial efficiency of the system as well as short term simulations to validate its power management capabilities. Feasibility is also key, meaning a proposed EMS is effective if it can be deployed on actual hardware and govern actual powerflows. It is thus, essential to study and construct a future EMS that will help the wide spread and successful incorporation of the latest renewable technologies.

Dansk Resumé

Da andelen af vedvarende energikilder øges i elproduktionen, er det blevet overkommeligt for husholdninger at etablere deres egen grønne produktion og blive prosumere. Regeringsincitamenter tilskynder også denne tendens gennem godtgørelse eller skattefradrag. I dag kan private forbrugere medtage adskillige enheder i deres opsætning, såsom: solcelleanlæg, batterier, små vindmøller, varmepumper osv. Motivationen bag disse systemer er primært at få økonomiske fordele af de reducerede energiregninger, men også at hjælpe i kampen mod klimaændringer. På grund af vedvarende energis ustabile natur er det dog vigtigt også at investere i et kompakt energistyringssystem (EMS), der styrer alt energiforbrug fra prosumere på en optimeret måde.

Disse systemer bruger sofistikerede optimeringsalgoritmer til at planlægge prosumers batteri eller Elektrisk Køretøj (EV)-opladningen. Fleksibilitet til at kunne inkludere nye fremtidige teknologier som varmepumper eller EV er et must. Denne afhandling har til formål at udvikle et EMS, der er i stand til at planlægge strømforbrug til prosumerens enheder, samtidigt med at elregningen minimeres, forbrugerkomfort er vedligeholdt og dem maksimale effekt fra elnettet er begrænset. Det kræver langsigtet analyse for at sikre systemets økonomiske effektivitet samt kortsigtede simuleringer for at validere dets strømstyringsfunktioner. Gennemførlighed er nøglen, hvilket betyder, at et foreslået EMS er effektivt, hvis det kan implementeres på faktisk hardware og styrer faktiske strømme. Det er således vigtigt at studere og konstruere et fremtidigt EMS, der vil hjælpe med at udbrede bredden og med succes indarbejde de nyeste vedvarende teknologier.

Nomenclature

Abbreviations

Abbreviation	Definition
ANN	Artificial Neural Network
ARMA	Auto-regressive Moving Average
BESS	Battery Energy Storage System
BiC	Battery Installation Cost
BrC	Battery Replacement Cost
COP	Coefficient of Performance
CP	Convex Programming
DG	Distributed Generation
DP	Dynamic Programming
DR	Demand Response
DSM	Demand Side Management
DSO	Distribution System Operator
EMS	Energy Management System
EV	Electric Vehicle
GA	Genetic Algorithm
GP	Grid Price
FIT	Feed in Tariff
HP	Heat Pump
IBR	Inclined Block Rate
LP	Linear Programming
LV	Low Voltage
MAE	Mean Absolute Error
MBE	Mean Bias Error
MILP	Mixed Integer Linear Programming
MPC	Model Predictive Control
MPPT	Maximum Power Point Tracking
NLP	Non-Linear Programming

Abbreviation	**Definition**
PAR	Peak to Average Ratio
POC	Point Of Connection
PSO	Particle Swarm Optimization
PV	Photovoltaics
RES	Renewable Energy Sources
RMSE	Root Mean Squared Error
RTO	Real Time Operation
QP	Quadratic Programming
SOC	State of Charge
SOH	State of Health
SWT	Small Wind Turbine
TSO	Tabu Search Optimization
WT	Wind Turbine

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1 Introduction

In the following chapter the research carried out is contextualized. The potential of an optimized Energy Management System (EMS) is explored in the background. The problem formulation and the objectives are stated providing a clear scope to the Master's Thesis. The fourth and fifth sections briefly describe the methodology and limitations of the project. The final section gives an outline of the report.

1.1 Background

One of today's world largest global problems, is the climate change. As it is now clear, human activities are the major cause [1]. Furthermore, according to the latest report from the International Energy Agency, electricity production is responsible for 41 % of the global CO_2 emissions [2]. To mitigate these problems, the energy sector is trying to turn green, by installing more and more renewable energy sources (RES), such as: Wind Turbines (WT), Photovoltaic (PV) plants, Hydro plants, etc. In 2017 RES accounted for 24.5 % of global electricity production which makes it the second largest source after coal (38.5 %) [3]. This impetus of green energy is mainly led by OECD countries, more specifically Europe, where the share of RES in electricity production is well above of the world average with its 33.4 % [3]. While other countries in the Middle or Far East are mainly relying on fossil fuels, there is a significant increase of Solar power installments in China, which is now the leader in total installed solar power, reaching 175.4 GW capacity [4]. These trends are often motivated by governmental initiatives as well, making it economically more beneficial to invest in green energies. One of the pioneers of these noble technologies is Denmark. Denmark is constantly increasing the penetration of RES and aims at 55 % of green energy in the total consumption. Moreover, the expected share of renewable energy in Denmark's electricity consumption is estimated to be 111 % by 2030 [5].

For a long time, traditional power systems has been relying on big centralized power plants producing electricity at medium voltages (10-20kV) with a constant steady frequency. The produced electricity is then transformed to higher voltages (100-500 kV) and transmitted through the transmission system. Arriving at bigger blocks of load, for instance cities, the voltage is transformed back to medium voltages and before the actual load, further down to low voltages (0.4 kV). This system assumes a unidirectional flow of power, from the generators to the loads, i.e. customers. Bulk power plants usually utilize high performance turbines with multiple MW of output power. These turbines have an important attribute, they are heavy rotating masses, that gives them inherent inertia. Inherent inertia of turbines is crucial for the steady and safe operating of a power system as it helps to keep the frequency stable during rapid changes on the demand side or sudden generation losses on the supply side. This is one of the many important ancillary services they provide, making current power systems reliable, stable and robust. Another important aspect is consistency, centralized power generation is highly coordinated and planned, thus its production is predictable. It is connected to the principle of any electrical power system: demand and supply has to met at any given point in time.

However, from a technical point of view, integrating such a big amount of RES into an existing power system poses difficult challenges for engineers and policy makers. Because of the volatile nature of RES, power plants based on wind, tidal or solar energy lack the predictability of their production which makes them less reliable. Moreover, solar PV panels or wind turbines naturally do not offer any inertia for the system, making the frequency vulnerable to the intermittent power fluctuations caused by these plants. Future power systems have to cope with all these problems to successfully incorporate green power sources. One possible solution could be the integration of shiftable loads such as Electrical Vehicles (EV) that can also offer flexibility to power systems [6], [7].

Parallel to these changes, which were mainly impacting the supply side and the medium to high voltage parts of the power system, the low voltage distribution level is also undergoing a series of changes. Rapidly evolving renewable technologies are providing affordable solutions for individual households as well. Thus, families, small businesses and other participants of the low voltage network, who were traditionally on the demand side, are now installing their own production of renewable energy and becoming prosumers. This is a significant change, since it makes the power flow bidirectional and blurs the line between demand and supply. For example, in Germany there have been more than 978.000 PV plants connected to the power system until January 2012, with an overall of 24 GWp. Out of this 24 GWp, 13 was directly installed on the low voltage network. 8.8 GWp of that was built up by PV plants which capacity were below 30 kWp, further emphasizing the up going trends of distributed generation (DG) [8]. Another study from Danfoss, states that PV plants directly connected to the LV grid account for $\frac{4}{5}$ of the total installed PV generation [9].

Prosumers are playing a major role in future power systems. However, their motivations are usually based on their own well being and usually neglect the effects they cause in the grid they are connected to. Main drive for prosumers is increasing self consumption and thus lowering their electricity bill. Financial gains are primary motivation for these types of installments. Certain countries offer support schemes which makes it possible to earn money on the sold power [10]. In developing countries like Middle East there are numerous renewable incentives by governments to serve as a motivator for installing new PV systems for residential use [4]. According to recent studies, in Europe the main drive for installing renewable generation at home, was to save on the energy bills [10]. In Australia, (which has one of the highest PV penetration (W/capita) in the world [4]) there are more than 15,000 businesses which have installed rooftop PV and they have saved a sum of $64 million on their electricity bills [11].

Wind energy has also found its way to the smaller scales and now becoming a valuable solution for prosumers residing in rural areas or farms due to their bigger electricity demand. Small Wind Turbines (SWT) are usually defined as a turbine having nominal active power output less than 50kW. The biggest markets are Asia and America, but it is expected that Europe will see a big growth as well in the upcoming years, thanks to the newly accepted policies promoting green energy [12]. In the US, small businesses and residents are encouraged to invest in their own green production, for example in SWTs, through various feed-in tariffs (FIT) [13]. Moreover, realizing the positive economical and environmental effects of SWTs, south American countries like Brazil, are looking at already establish SWT markets like the US as an example, to build their own infrastructure [14]. Countries like Denmark has accumulated a significant amount of Know-how and knowledge on Wind Power [15], not only in MW scale but also regarding the market of SWTs [16]. Moreover, the Danish SWT market is constantly looking for international expansions, outside of Denmark, for instance, in Canada [17].

As the number of options for prosumers regarding electricity production is rising, so does the different ways to consume that electricity and swap other primary energy sources as well. Heat pumps (HP) are on a globally rising trend among residential households for supplying the thermal needs of the family with the means of electricity. According to a recent study, wide spread implementation of HPs in Europe, can reduce the overall CO_2 emissions associated with heating and cooling in buildings by 47% from 2012 until 2030 [18]. This would be a remarkable result, since energy demand of buildings is responsible for the 25 % of total CO_2 emissions in the word [2]. Utilization of HPs is especially possible at rural areas where central heating is not available or gas pipe lines are out of reach [19], [20]. This trend is also motivated through governmental initiatives [21]. For instance, in Denmark, consumers with HPs can benefit from reduced electricity taxes. Denmark is taking HP into account for its 2030 and 2050 energy goals as well. It is expected that just for district heating HPs will provide 12% of the total heat demand [5]. Furthermore, Münster at al. state in their report that individual heat production in Denmark will completely move from using oil and natural gas in 2010, to HPs in all the scenarios they analysed for 2025 [22]. Similar results were obtained in [23], where researchers concluded that residential HPs will be providing 66–70% of heat production from individual heating sources, which is the 24–28% of the total heat demand after the year of 2035.

Another flexible load which is recently gaining more attention is EV. To limit the green house gas emission, the EU countries have restricted the CO2 emission for the internal combustion vehicles (ICV). As a result, car manufactures are increasing the production of vehicles that will help them to fulfill the set requirements. EVs hold potential to reduce CO2 emission and are considered a key factor in mitigating the climate change [24].

The rapid development of battery technology reduces the EV's price and makes them more attractive for consumers. For urban transportation there is no longer a need for compromising the vehicle's range when switching to EV from ICV. As a result, the number of EVs in the market is growing rapidly and is expected to increase in following years [5]. It is expected that the number of EVs in Denmark will be around 350,000 by 2030 [5]. The necessary power to charge an EV has to be both provided and transferred by the grid. The increase in generation required to satisfy the increase in demand is generally not considered a problem. However, the distribution's grid capability to transfer this increased energy poses a potential problem.

The currently existing grid infrastructure is designed to last 30-50 years. As a matter of fact some of the elements, like cables might be at the peak of their possible loading, as they were designed almost 30 years ago [25]. Therefore, transferring more power in the grid might not be possible at peak loading hours because of the limited current carrying capabilities of existing cables. Hence, it is necessary to investigate solutions that do not require an early grid reinforcement of electrical infrastructure, but optimizes the utilization of already existing grid infrastructure. Electricity demand follows the trend of the daily routines of the residents in the household. In Denmark the peak electricity demand is season dependant but occurs in the evening, when people are usually at home [26]. Superimposing the possible power consumption by EV's on the demand, the grid may experience overloading problems. Residential EV chargers connected to the household can draw AC power up to 11 kW when used, resulting in peaks in the electricity consumption. Thus, deciding on the charging hours for the EVs has a huge impact on the overall electricity demand of a house and can potentially mitigate the stress imposed on the low voltage grid.

A possible solution that maximises the potential of integrating RES such as PV or WT as well as EVs to the existing technology could be to install an Energy Storage System (ESS).

Among the different types of solutions, Battery Energy Storage System (BESS) is a strong segment, along with the Thermal Energy Storage (TES) system. In 2019, Europe experienced a 5% growth in the behind-the-meter storage market which were mostly residential installations [27]. In Australia 233 MWh of new home batteries have been added in 2019 to reach an overall of 1 gigawatt-hour (GWh) of residential battery capacity, but the same trend can be seen in Germany where the total residential BESS capacity has reached 369 MWh in 2019 [27].

The report from the energy department of the Sandia laboratory provides a summary of applications and benefits that network-attached storage can bring, regardless of the capacities [28]. This document generally serves as a reference to identify the different applications. They are classified according to whether the benefits apply to the manager network or individual. A special category is added in case the storage is associated with a renewable source of production. The European "Grow-ders" project, that targets to demonstrate the feasibility of grid-connected storage, also proposes a classification of the applications [29]. It should be noted that the majority of applications proposed in [28] and [29] are not economically valued with current and future energy tariffs for the next twenty years. However, the work carried out in these studies can be utilized to choose a relevant application for the system and in the economic context considered.

All these trends are pointing into one direction, prosumers have complex (even more in the near future) energy systems in their household, including various sources of electricity generation, flexible loads in the form of EVs or HPs. However, challenges arise along these systems as well. First of all, the volatile always changing nature of RES makes them hard to match with the local consumption. Their usual production profile does not follow the load profile of a typical household. Figure 1.1 depicts typical load and RES profiles for a general household located in the United Kingdom (UK) on a winter day.

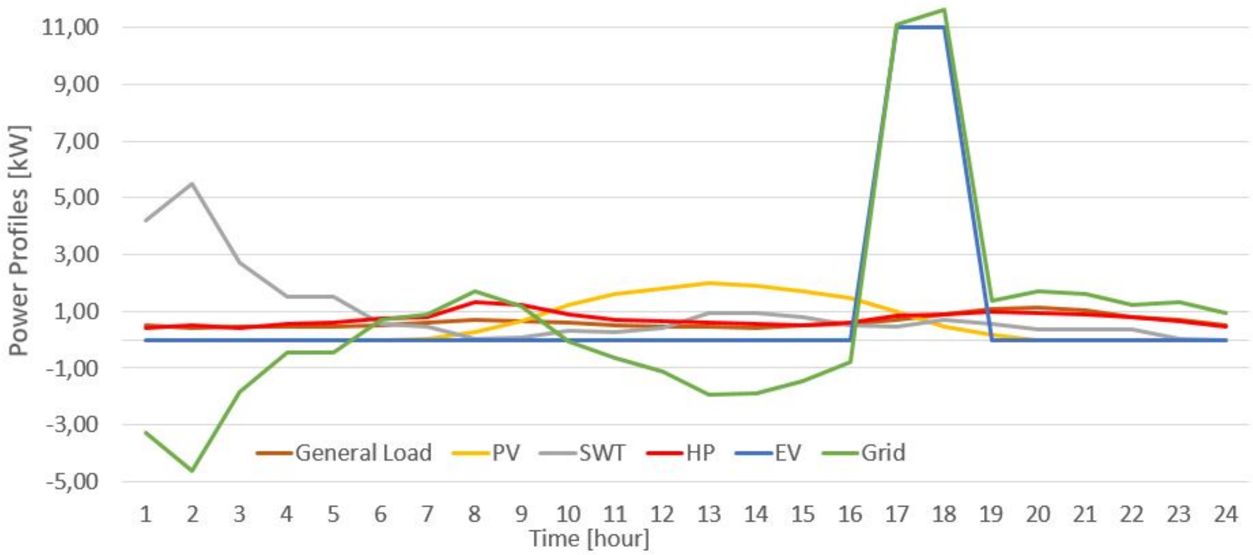

Figure 1.1: Typical winter daily profiles of a general household load, HP electricity demand [30], solar power [31], SWT output [32] and EV charging power

The solar power and the wind power are produced by a 2 kWp PV panel and a 10 kW SWT respectively. Additionally, there is an EV plugged in for charge at 17:00 and continues charging with a fixed 11 kW for 2 hours. The HP load is more or less following the general load of the household, peaks in the morning, flattens out during the day and peaks again in the afternoon/evening. PV production is mainly happens outside of peak hours while wind is strongly fluctuating along the day. Power exchanged between the house and the grid is plotted with green. It shows that production and demand is clearly not met instantaneously. Moreover, EV causes a large peak in the afternoon when other loads increase as well, while RES production is pushing power to the grid when consumption of the house is generally low.

As mentioned BESS could help mitigate this problem, but it needs proper scheduling in order to make the investment worthwhile, since FITs are much lower (especially in Denmark) than the actual price prosumers pay for purchased electricity, due to the various applicable taxes. This means, delivering huge amounts of energy into the grid without utilizing it locally, while buying electricity during high price hours, can cause serious economical losses for the prosumer. On top of that, as previously mentioned EVs and HPs are loads with special time schedule. The former one is following the travelling habits of the inhabitants and causes large consumption peaks whenever charged. The latter one is bound to the thermal demand of the household which is highly dependent on seasons but also more easy to schedule as inhabitants always require a minimum temperature. Moreover, household connections are limited at their point of connection (POC) in terms of maximum current per phase [33].

All of these problems, heavily constrain the usage of RES and the potential of prosumers and highlights the necessity of a governing system. A system that manages all the devices and power flows of the prosumer, achieving optimal RES and BESS usage, while ensuring user comfort and grid constraints is a must for the prosumer. A system capable of achieving all of the before mentioned, is called an Energy Management System (EMS). It is a newly emerging term, strongly connected to the concept of Smart Grid [34]. Utilizing the large amounts of RES built into the system in forms of DGs and new technologies like EVs and HPs are the basis of any future power systems [35].

Prosumer based EMS is gaining more and more interest all over the world. There are multiple structures, when it comes to the implementation like: grid-connected households with offsite DG, off-grid houses, small businesses and commercial buildings equipped with onsite RES and/or flexible loads or even industrial prosumers [36]. But the most common is a grid-connected household with onsite PV, storage, and/or flexible loads just like described above. There are already going projects and products available on the market like tiko [37], which promises 10% energy bill reduction and a user friendly environment to optimize the power flows of the prosumer. Geo's products offer a wide range of smart solutions including solar power and load demand monitoring along with heat pump control in a form of a smart thermostat [38]. Other solutions are focusing on the grid support side. Smart grid technologies are emphasizing energy efficiency, DGs, data share and utilization of existing grid infrastructure [39]. For all the mentioned above, an optimized EMS provides the perfect solution. Thus, it is of major interest to develop an optimized, flexible, efficient and reliable EMS for prosumer utilization which takes all the previously mentioned aspects into account.

1.2 Problem formulation

The trends in the daily PV profiles or wind profiles are not predictable. The ambient temperature also changes according to seasons. This intermittency of the RES makes it challenging to fulfill the load demands instantaneously, necessitating an efficient EMS with energy storage units such as BESS. The power flows within the different components of the EMS as well as with the grid should be optimally governed to result in potential financial benefits to the prosumer. The efficiency and the robustness of such EMS along with the energy bill minimization can prove lucrative to invest in such solutions.

It is also important to consider user comfort when integrating new technologies such as BESS, SWT, EVs and HPs. It would be desired to have the EVs charged by the morning to be ready to go for the day. Also, it would be ideal to have the heat setting inside the house to a convenient range of 20 °C to 24°C depending on user's choice and weather conditions. The EMS has to schedule the charging of EVs and also the temperature settings for the house via the HP. Thus, to ensure the user comfort it is necessary to formulate constraints accordingly. Apart from this, it is also important to have a reliable forecast for Solar Irradiance (G), wind speed, dynamic electricity prices, general loads and thermal loads of the household.

Grid constraints as mentioned in Section 1.1 should also be complied when optimizing EMS and its interactions with the external grid. Also, it is desired to ensure the flexibility of the EMS for possible inclusion of future technologies or additional constrains posed by the prosumer. These systems have to be flexible in terms of the capability of handling various scenarios which could arise from varying loads, different grid prices, fluctuating production, number of connected devices or battery state of charge (SOC). Studying these scenarios help in the development of a reliable EMS which would prove efficient and profitable in long term.

The overarching challenge of EMS can be formulated as follows: "*How to design a household energy management system that can schedule BESS and EV charging while taking into account the prosumer's RES production, general load and heat demand and dynamic prices while ensuring its user comfort and compliance with the connected low voltage grid?*".

1.3 Objectives

This thesis focuses on EMS for the residential sector, in the context of a liberalized electricity market with financial benefits for renewable energy production. The proposed EMS should be suitable of harmonizing different types of RES (PV, SWT) with the help of BESS, while ensuring user comfort (thermal load, EV availability) and grid compliance.

The final objective is achieved through 4 main goals:

- To design and verify a suitable EMS algorithm that accounts for techno-economic constraints as well as end-user comfort and habits.
- To quantify economic benefits for end-user.
- To consider the effect of battery degradation to protect the battery from premature aging.
- To validate the proposed algorithm on a laboratory setup.

1.4 Methodology

The EMS optimization was performed with the help of MATLAB/Simulink. The algorithm was designed using MATLAB to provide the optimal day ahead power schedules. Following that, it was tested in Simulink. The validation of the algorithm was performed at Smart Energy Systems Laboratory in Aalborg University using MATLAB/Simulink and relevant components along with their interfaces (see Chapter 6).

The measurements of solar irradiance, wind speed, ambient temperature were obtained from the weather lab at Aalborg University (with minutely resolution) [40]. The dynamic electricity prices were obtained from Nordpool [41]. The data sheets and ratings for commercially available components are used to parameterize the models for PV, SWT, EV, BESS and HP.

1.5 Limitations

During the development of the EMS algorithm, in order to keep the focus and scope of the thesis, certain aspects has been simplified or neglected. Therefore, the following limitations have been considered during the work:

- Only active power consumption and production is addressed, reactive power flows are neglected, i.e. $cos\phi = 1$ is considered.
- Household is assumed to have 3 phase electricity and all the discussed assets are connected to all three phases. Furthermore, the power flows are assumed to be evenly balanced between every phase.

- Load shedding and scheduling of loads are not considered.
- Predictive scheduling assumes that 24 hour weather forecast is available.
- Detailed EV and house thermal models are considered out of scope.

1.6 Outline of the Project Report

This thesis has been divided into 7 main Chapters. Chapter 1 describes the motivation as well as the fundamental background of this thesis, defines clear objectives, lists limitations and formulates methodology. Chapter 2 overviews a great number of existing literature on EMS and their implemented optimization techniques. It also analyses their qualities, pros and cons as well as their feasibility. Finally, it proposes a suitable method for EMS application considered in this work. Chapter 3 defines the components of the proposed system and features a base case scenario which highlights the importance of EMS. Chapter 4 presents the selected optimization technique and its implementation for the proposed EMS. The developed algorithm is tested in a long term analysis and its results are discussed. Chapter 5 develops 2 types of dispatcher approaches, lists the models used for testing, then shows the effects of varying different parameters in the algorithm. Chapter 6 showcases the laboratory setup, its components and the results obtained from the validation process. Chapter 7 summarizes the main challenges and remarks of this thesis and suggest questions to be assessed in the possible future. Appendix A lists the yearly data for PV, SWT, etc... used in Chapter 3 for base case. Appendix B contains results of year long analysis of EMS. Appendix C shows the results of fine tuning the short term forecasting. Appendix D gives the input data for dispatcher verification in Chapter 5 and shows the results of the conducted tests on the dispatcher algorithms in Chapter 5.

2 Optimization of Energy Management Systems

In this chapter today's concept of EMS is presented. The purpose and elements of such systems are described. An overall literature review on the most used optimization algorithms in EMS is carried out. Advantages and disadvantages are listed and practical implementation possibilities are examined. Based on the available studies and approaches, a suitable method is chosen to implement in this thesis.

2.1 Overview on existing EMS solutions

As shown in Section 1.1 the number of DGs in the low voltage grid are on the rise. To cope with this challenge Smart Grid solutions has been developed and proposed in large numbers over the past years. The future backbone of Smart Grids are prosumers [35], as they contribute to both supply and demand. Therefore, it is essential to ensure the reliable, cost efficient and safe operation of these systems, evoking the idea of EMS.

EMS became a highly researched area during the last decades. The field of applications seems to be infinite, ranging from remote off-grid systems in Africa, maritime systems on large ships or self-supplying office buildings to islanded power systems. The need of a self governing system with optimal energy usage is especially important when it comes for residential implementation, since it is responsible for approximately 30 % of overall electricity consumption [42].

The purpose of any EMS is to maximize or minimize the objective functions, which could include: energy cost, carbon footprint, efficiency, user comfort, reliability, self consumption, power quality, losses, peak sheaving, grid support, etc [34] [43]. In order to achieve these goals, numerous solution approaches have been developed, resulting in optimal and efficient EMS for the prosumer.

The core element of any functional EMS, is the underlying optimization method. It can be as simple as a rule based decision making tree which tries to minimize the grid power based on actual real time power flows of the system [44]. More complex methods take into account future forecasts as well, such as: Rolling Horizon [45], [46]. Other researchers proposed EMS solutions which make their own prediction based on past events and collected data by using, for example, machine learning approaches [47].

However, most EMS optimization studies can be categorized into two groups based on their implemented methods. The two biggest branches are distinguished by the quality of their solution: Exact or Approximate. Exact solutions are provided by mathematical approaches like:

- Linear Programming (LP)
- Quadratic Programming (QP)
- Convex Programming (CP)
- Non-Linear Programming (NLP)
- Dynamic Programming (DP)

These are equation based, analytical techniques and have a great history in optimization. While the other group is mainly consists of numeric solutions and can be Heuristic or Meta-heuristic:

- Genetic Algorithm (GA)
- Particle Swarm Optimization (PSO)
- Model Predictive Control (MPC)
- Artificial Neural Networks (ANN)
- Tabu Search Optimization (TSO)

A brief classification of these optimization techniques is summarized in Figure 2.1.

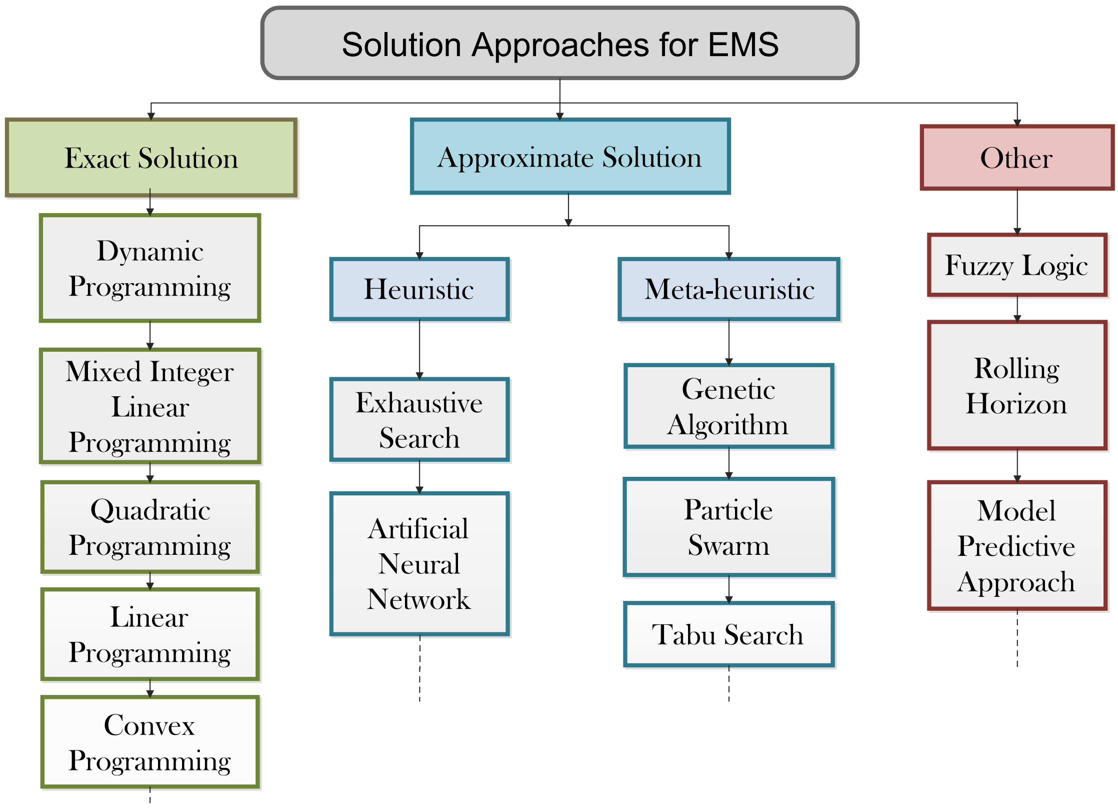

Figure 2.1: Taxonomy of Optimization Techniques

The exact methods are generally based on mathematically deriving the optimal solution. These methods guarantee an optimal solution. However, they are not always ideal to use as they require more time and computational effort. Moreover, it is not always needed or possible to find the exact solution for the optimization problems. In such scenarios, approximate methods are utilized. These methods calculate the satisfactory solution in lesser time. However, their solutions might not be optimal.

EMS solutions utilize different assets of a prosumer's household, one of the most popular ways explored in literature is Demand Side Management (DSM) techniques. The DSM techniques focus on maintaining the balance between supply and demand. Two main types of DSM techniques are load management and demand response (DR) [48]. Load management techniques generally target to prevent blackouts or major distresses to the grid constraints while still improving the overall energy efficiency. Load management might benefit the grid in terms of flexibility [49]. Whereas, DR refers to a decisive action taken by the prosumer to benefit from the dynamic electricity price models. The prosumer and electrical utilities are major beneficiaries of this technique. However, the volatility of loads can endanger the grid integrity within seconds and thus it is important to tackle uncertainties in the load variations or possible renewable productions when applying DR [50].

These approaches usually focus on shifting the use of appliances to off-peak hours [51]. These type of strategies must take into account additional criteria such as user comfort and Peak to Average Ratio (PAR) in order to ensure that the scheduling of loads doesn't disrupt the user's routine as well as the ratio of the peak load to the average load [51].

Distribution grid utilities generally charge something called an Inclining Block Rate (IBR), which is a slightly higher than normal electricity price when total electricity consumption exceeds a certain threshold. It is considered in some literature that includes real time dynamic electricity prices [48], [52].

In the next sections, the existing literature on EMS applications based on the above mentioned solutions is reviewed. The focus is put on advantages and disadvantages of certain methods, to select the most suitable one for the goals of this present thesis work.

2.2 Mathematical approach

The more traditional way of optimizing problems is to use a mathematical programming or equation based approach. It requires to model the targeted system based on their behaviour expressed in mathematical terms. Usually these methods are hard to solve and can require considerable amount of computational power. They need proper attention while selecting the optimization horizon and number of included devices as dimensionality is one of their major drawback. On the other hand, depending on the applied method they can have continuous or discrete, binary or non-binary variables. They provide exact solutions and do not require training data which makes them flexible in terms of applicability. Solutions can be deterministic or stochastic to account for uncertainties in the forecast.

LP problems formulate the objective function and constraints as strict linear relationships and usually implemented as a Mixed Integer Linear Programming (MILP) problem. Advantages of LP are their relatively low computation demand and the commercially available softwares (AMPL, CPLEX, LINDO, etc) utilizing well known solving methods (simplex, branch and bound, etc.) which can solve LP problems. Weaknesses arise from the linearity as well, the level of accuracy of a linear household model is lower and might not be sufficient for all EMS purposes.

In [53] authors develop a MILP based EMS for a microgrid containing PV, a WT, BESS, microturbine, fuel cell and some loads. They pay special attention to the uncertainty of RES and load describing it with their probability density function. Their algorithm is capable of scheduling the dispatchable generation units while decreasing the fluctuation in the BESS power output. However, the financial gains are not assessed and its also lacking a long term analysis as they only account for 24 hours.

In [54] the focus is on EVs and their capabilities in terms of bidirectional energy flow considering an office building with PV panels on the roof. The objective is to minimize the daily electricity cost of the building, by efficiently scheduling every EV and the BESS under dynamic prices and FIT. It was proved that taking stochastic approach can significantly reduce the power bill compared to the deterministic approach. On the other hand, the battery degradation of the EVs as well as the BESS were not taken into account resulting in more charging and discharging cycles which can lead to the decrease of life expectancy of the batteries.

Francesco et. al. [55] describes a house with both electrical and thermal loads, where HP is used along side with PV and energy storage. The MILP solution in [55] is able to effectively schedule tasks on the load side and prioritize them according to the constrains applied. Their EMS has achieved 50.4 % cost reduction compared to the case where no EMS was applied. MILP is also suitable of sizing the HP and generation units (PV, SWT, etc) as Beck et al. shows in [56]. Their work concentrate on the financial aspects of such prosumer set up assessing various scenarios regarding different FITs schemes, electricity prices and consumption profiles, while a MILP based EMS ensures the minimization of "annualised discounted costs". The results conclude that optimal PV size is highly dependent on the household load while the optimal HP size is mainly independent of the FIT and electricity price. However, it is unclear from the work how the actual optimal sizing is done.

In [57] authors focus on demand side management solely. Considering 4 different energy price scenario and 3 different appliances the possible daily cost reduction is 10 %. The paper shows that utilizing an EMS and optimization, significant saving can be achieved even without having onsite production. An extensive and thorough study is done in [58] considering a wide range of user appliances, BESS, PV, heating and gas consumption. A MILP optimization has been deployed in order to minimize total cost of electricity, demand, peak load and emission. The results are 20% decrease in energy cost and 50% reduction on the peak load. The authors state that there are several pilot programs implemented but results were not available at the time of publish.

Quadratic Programming (QP) and Convex Programming (CP) based optimization methods are mostly employed when there is a good understanding on the studied system conditions [34]. In QP, the objective function is formulated as a quadratic function. For CP problems it depends on the objective itself, minimization problems are formulated with a convex objective function. While maximization problems have concave objective functions. As for the constrains, QP utilizes linear constraints, CP works with convex equality constrains and concave inequality constrains [43]. The computation time of QP is still low compared to other methods, but achieves greater accuracy then simple linear approaches duo to the quadratic objective function [59]. Where LP is applicable, so is CP as all linear functions are convex also. Moreover, CP has a guarantee of converging if the solution exist, but it is more complex than LP or QP. Jia et. al [60] developed a multi-stage, multi-scale optimization framework for home energy management. QP was used to solve the quadratic objective function for the hourly scheduling stage, considering deferrable EV charging, non- and interruptable loads. The proposed optimization was able to achieve 20% cost reduction compared to their benchmark method. In [61] a real-time pricing algorithm with load uncertainty was developed to provide a real-time price signal for EMSs. The cost function was formulated as a quadratic function and the work proved that load uncertainty increases the optimal price.

Amir et. al [62] proposed a cooperation between several households, all of them equipped with EMS. Every individual EMS would aim for cost minimization (formulated as a CP problem) alongside with PAR minimization (formulated as a simple LP problem). The results show, by working together and sharing their optimal schedules, a global optimum in the whole system can be achieved which is the most beneficial for everyone. CP was effectively utilized in [63] to optimize the sizing and scheduling of a residential BESS for a household equipped with EV and PV. The authors showed that utilizing bidirectional powerflow between the house and EV can yield in 2.7 % reduction in daily electricity cost.

NLP solutions are extended versions off the LP approach, making it possible to formulate constrains and objective functions in a non linear way and thus non linear models can be used in EMS resulting in more accurate results. Nonetheless, it comes with greater complexity and computational burden. Anand et. al [64] proposes an EMS to optimally schedule EVs, DGs and responsive loads in a microgrid. The developed "priority-based price-sensitive" scheduling of EVs proved to be effective and yielded in a 6.17 % total operation cost reduction. Stluke at. al [65] conducted that developing EMS for future microgrids (campuses, hospitals, neighbourhoods, etc) is a large scale optimization problem and the most suitable approach in their opinion is the Mixed Integer Non Linear Programming. Their paper formulates guidelines on energy storage and DG integration, demand side management and overall energy usage optimization.

The most flexible approach among all mathematical methods is DP. It was proposed by Richard Ernest Bellman [66] in the 1950s to solve decision processes. It started to become popular in EMS applications due to its effectiveness on nonlinear, nonconvex or even mixed-integer problems. The basic principle of DP is to break the original optimization problem into sub-problems (stages) and solve them sequentially resulting in the optimal solution for the original problem. This recursive process makes it effective for scheduling problems. Moreover, since DP is storing the sub-problem solutions, it provides additional information for real time operation (RTO) and handling uncertainties. However, it suffers from dimensionality, meaning that increasing the optimization parameters (states) or the optimization horizon, will result in exponentially increased computational burden. DP was used to minimize the daily energy cost of a household by utilizing EV as a BESS in [67]. To reduce the computational burden the authors have proposed a state-independent 4 threshold battery scheduling policy.

Matteo et al. considered demand response as the main source of energy management in [68]. Dynamic prices and EV were also taken into account, while DP was able to achieve a 17 % peak load reduction. However, authors fail to explain what the exact financial benefit or motivation of the prosumer is. The proposed EMS by Henning et. al [69] involves EV, fuel cell for heat and electricity cogeneration, demand response, PV, BESS and a thermal storage system. Their objective function is flexible and can target any of the following: cost minimization, carbon footprint minimization, EV availability maximization or maximization of BESS life expectancy. Focusing on cost minimization the EMS improved the base case from 0.46 $ to -2.39 $, meaning that it earned a profit of 2.39 $ by optimal power scheduling.

Similar solution was developed both in [70] and [71], where DP based EMS was deployed at a prosumer to optimally schedule their PV+BESS under dynamic pricing. Both works have taken into account battery degradation as well, the achieved cost reduction was reported around 13% in both studies. Tùng et. al in their work [72] analysed the effect of uncertainties in dynamic prices on optimized demand respond. Authors claim that their proposed policies can save up to 40 % on the energy bill, which is a significant remark.

Table 2.1 contains a summary on the discussed mathematical methods.

Table 2.1: Literature review on EMS using mathematical optimization

Method	References	Advantages	Drawbacks	Limitations	Computational Burden	Flexibility Constraints	Flexibility Objectives
LP	[53][54] [55][56] [57][58]	Simple, Available solvers	Inaccurate	Only linear problems can be solved	Very Low	Linear, Easy to expand	Linear, Usually single
QP	[60][61]	Relatively simple, Accurate	Can be an NP-hard problem	Only quadratic cost functions can be used	High	Linear	Quadratic
CP	[62][63]	Simple, Guaranteed global optima	Require convexity test	Only convex functions can be used	Low	Linear and concave	Convex, Easy to expand
NLP	[64][65]	Wide range of application, Generality	Complexity	Solution not guaranteed	Very high	Any	Any
DP	[67][68] [70][69] [71][72]	Guaranteed optimum, Effectiveness	Curse of dimensionality	Discrete values only	Very high	Any, Easy to expand	Any, Easy to expand

2.3 Heuristic approach

Heuristic refer to computational process that calculates the optimal solution by improving the candidate solution 'iteratively' respecting a given measure of quality [73]. Heuristics are problem-dependent techniques and the particularities and constraints of the problem needs to be adapted each time these methods are enforced. Heuristics are too greedy in their search for the optimal and often get stuck at the local optimal and fail to provide an optimal solution. On the other hand, meta-heuristics are problem- independent techniques. Often times, they do not benefit from the particularity of the problem and can be utilized as black boxes (although some minor fine-tuning of intrinsic parameters is required). Unlike heuristic approaches, they are not so greedy in their search for the optimal solution. In fact some meta-heuristic techniques (For example, Simulated Annealing technique) also allow limited deviation in the solution to meticulously explore the search space for better solution. In this process, it is more likely to end up with global optimum compared to heuristic approaches. In general, meta-heuristic techniques do not require the objective function to be convex and are thus computationally robust [74].

Heuristic approaches can prove effective in terms of reduced complexity in terms of providing approximate optimal solutions when applied to an EMS. A lot of literature has utilized heuristic approaches to optimize an EMS. For example, One of traditional techniques used for finding an optimized solution for the given problem is Exhaustive Search Methods. This techniques evaluates the value of the objective function for every possible point from the predetermined set and chooses the best option. Although simple, This technique requires large time to process [75].

In general, nature-inspired optimization techniques fall under meta-heuristic category [76]. Swarm based optimization (such as PSO) and evolutionary algorithms (such as GA) fall in this category. Rahim et.al. presented a comparative analysis on exploiting different meta-heuristic methods such as GA, Binary Particle Swarm Optimization (BPSO) and Ant Colony Optimization (ACO) to evaluate the performance of a household EMS with respect to minimizing the overall electricity bill and PAR and maximizing the user comfort [48]. The study proved GA based EMS as more effective than BPSO or ACO based EMS. Also, the study was conducted to include multiple users (ranging from a single home to 50 homes) to validate possible scalability of the technique .However, the human behaviour of the residential load was modelled mathematically. The authors also mention improving privacy and security between the end user and utility as a future work.

Elsied et. al. propose a real-time EMS for microgrid. The authors utilize GA to minimize the electricity bill as well the carbon emissions and maximize the power of available RES. The RTO of the EMS is acheieved with simulation tools such as MATLAB-dSPACE Real-Time Interface Libraries (MLIB/MTRACE). A micro-turbine, fuel cell, wind turbine, loads and storage unit are considered for the simulations. Interestingly, the hardware implementation of the proposed EMS is achieved in a laboratory test bench. However, the inclusion of future technologies such PV and EVs is not considered in this study [77].

Zhao et. al. model a household EMS that uses GA optimized DR to reduce the PAR and electricity bill. The authors use real-time pricing (RTP) with the inclining block rate (IBR) model to successfully lower the electricity bill and PAR for a simulation period of three months [52]. However, the study does not consider the integration of RES or emerging technologies like EVs and does not ensure user comfort.

Cordero et. al. adopt a modified version of BPSO to find the optimal distribution of energy resources in a green smart house [78]. This algorithm mainly targets to balance the load distribution in the house. The house is powered by PV, WT as well as traditional energy sources and the load balancing aims to reduce the electricity bill and maximizing the usage of green energy. This study however lacks in considering the user comfort and integration of future technologies such as EVs.

The Model Predictive Control (MPC) strategy takes into account the uncertain environment of generation and consumption profile with certain realistic constraints [34]. However, MPC based methods come with higher costs for modelling as they need a detailed model of the plant, data acquisition from the plant, along with the implementation of required observers, expert monitoring and deployment [79]. This limits the application of such methods to medium-large buldings. Mbunga et.al. used an MPC optimized EMS for a commercial building to minimize the electricity bill based on peak, off-peak and standard electricity tariffs. The given MPC proved to be effective to include numerous constraints and it was possible to reference tune the parameters to show the variations in optimal cost of electricity paid [80]. However, RES were not included as the power sources.

Artificial Neural Networks (ANN) utilize supervised training techniques to solve scheduling problems [34]. ANNs are often used in the literature to tackle scheduling of appliances when it comes to DSM techniques[43]. Neural networks are also widely used for forecasting energy from volatile energy resources such as RES. Megahed et. al. applied neural network predictive control to an EMS in zero energy building [47]. In this study, ANN and MPC are combined to reduce disturbances and enhance control for a seven months, with the main objective of making the building self-sustainable. Although the study was extrapolated to 15 years, there was no hardware implementation in any field experiment. Also, battery degradation was not considered.

Table 2.2: Literature review on EMS using heuristic optimization

Method	**References**	**Advantages**	**Drawbacks**	**Limitations**	**Computational Burden**	**Flexibility** Constraints	Objectives
GA	[48][52] [77]	Simple, Available solvers	Inaccurate, Approximate solutions	Not suitable for long-term analysis	High	Easy to expand	Any
PSO	[48][76] [78]	Can be used as a black box model	Approximate solution	Low convergence rate	High	Moderate	Any
MPC	[80][79]	Accurate	Complex	Requires exact model of the building/ plant	High	Moderate	Any
ANN	[43][47]	Detailed models are not required	Requires large amount of data	Requires lot of processing time	Very high	Moderate	Any
TSO	[81][82]	Semi-deterministic nature	Complex	Can result in inaccurate solutions	High	Easy to expand	Any

Tabu Search technique uses the memory structures to avoid getting trapped in the local optimas [81]. Arefifar et. al. propose an EMS with multiple RES (PV,biomass and Wind) an ESS and EVs for a microgrid operation [82]. The authors use Tabu search algorithm for optimizing the EMS to reduce the electricity bill. Different sensitivity analysis are performed to account for uncertainties in loads and generation. However, a single day is used for simulation and battery degradation is disregarded. Tabu search method is famous for its semi-deterministic nature. As it acts both as a local and global search method [83]. Table 2.2 contains a summary on the discussed heuristic methods.

2.4 Discussion and Practical Considerations

The literature available for EMS optimization mostly deals with shorter duration of offline simulations ranging typically from a day to a week. Only one assessed a time interval longer than a month [47]. However, in order to capture the financial gains it is important to perform long term simulations ranging from a few months to years. It is a key step in order to prove these solutions a worth investment in the eyes of the prosumer.

When performed for longer duration it is also important to consider the degradation endured by the battery in case BESS is opted as an ESS since the repeated charging and discharging cycles can cause premature battery aging [71]. Without accounting for the degradation, EMSs tend to include several cycles a day to ensure energy cost minimization, which can cause more harm in the long run. Thus, it is vital to include this phenomena if a reliable and effective EMS is to be constructed. However, most of the papers considering BESS for household EMS applications do not include the battery degradation costs.

To easily accommodate this term (and any others) it is desired to select an optimization technique that is flexible to adapt new constraints and multiple objectives. The selected method should make it possible to easily integrate any new technology, or requirement from the prosumer in the future, without having to rebuild the whole algorithm. Methods like LP or CP would make this difficult, since if a new objective, model or constrains are introduced, first they would have to be converted into linear or convex forms. Such a conversion requires compromises or often simply infeasible. NLP, DP or heuristic methods can offer this kind of flexibility.

The given optimization strategy should also be effective for a household setup. Recent techniques such as MPC are effective for applications on medium-large scale buildings (commercial buildings) as they require detailed system models with implementation of observers, expert monitoring and deployment options [79]. Other techniques like ANN require large amounts of data and powerful PCs to effectively train the neural network. Data and computational power which is usually not available for a household prosumer. Simpler mathematical approaches however, can be run on average household PCs with a RAM requirement of 1-4 GB and without the need of any training data in a matter of seconds [53], [55].

Although numerous papers have utilised heuristic or meta-heuristic approaches to tackle the optimization of EMS, these approaches do not provide exact solutions like mathematical approaches. With heuristic approaches the search for optimal solution is not guaranteed. Meta-heuristic approaches on the other hand are often used as black box models (with minor fine tuning of the intrinsic parameters) which compromises their flexibility and adaptability to new constraints [78]. Also, it can be challenging to initialize these methods and they might converge prematurely in case the stopping criteria is met.

Another common issue with the available EMS studies is the actual feasibility. Successful simulations and offline schedules are presented for 24 hour scenarios with a typical time resolution of 15 minutes. Majority of papers do not consider the hardware deployment. Every schedule is based on forecasted values no matter if the approach is deterministic or stochastic. Day ahead schedules has to be adapted on a minute level to regulate electrical properties (power, current, voltage) in reaction to the actual instantaneous consumption, RES production and heat demand. This would require an algorithm which is able to optimally schedule for the future (based on forecast) and then able to adjust that schedule according to the running operation.

2.5 Summary

Based on the all the aforementioned criteria and observations, DP has been chosen as the core optimization method for the proposed EMS in this thesis. One of the biggest advantage of DP, is its great flexibility. DP allows to implement any objective function (linear, non-linear, convex, etc) and constraints, but unlike NLP it always yields in a optimal solution. It requires no prior knowledge of the RES production or prosumers load profile. Its flexibility also makes it easy to build a modular system, where different devices (PV, SWT, BESS, HP, EV, etc) can be integrated or disconnected with ease. New constraints (to account for new grid requirements, prosumer habits) can be added any time without an effort. Moreover, constructing the day ahead schedule using DP provides additional information for sub-optimal solutions, which can be reused during the running operation as a base of a new schedule, if production or consumption deviates from the predicted values.

Disadvantages of this method is the curse of dimensionality. As the number of stages and optimization variables start to increase, the required computational burden grows exponentially. However, for EMS applications, to capture the important behaviours and provide enough accuracy, DP does not stand severe computational requirements [71].

The selected method contains all desired aspect, it is a proved and efficient method for scheduling problems and fits perfectly in the EMS structure. Its flexibility and reliability makes it the best choice among the analysed methods.

3 System Description

This Chapter describes components that are involved in the system, their sizes and a brief description about their working. Two main parts of the chapter are the following: to establish and define the system in which the EMS will be deployed and to propose a base case scenario that shows the interactions between these system components without any EMS.

3.1 System Components

The given system consists of production units namely, SWT and PV panels. The load contains a HP, EV and the rest of the load of the household. The household is also equipped with BESS. Figure 3.1 shows these components. The POC refers to the point of connection with the grid. It is also assumed that weather forecast and dynamic electricity prices are known. Appendix A lists electricity prices and the recorded weather data for an entire year.

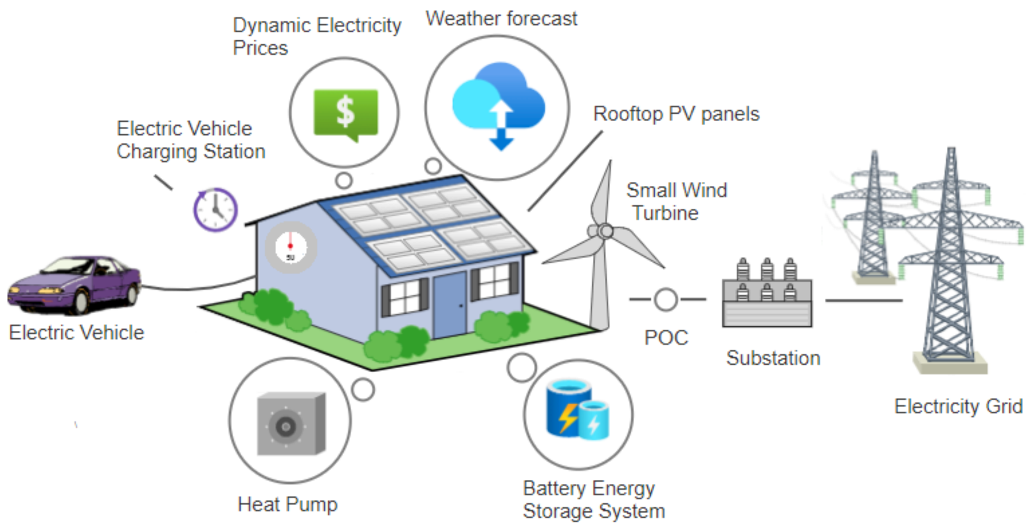

Figure 3.1: Configuration of a smart prosumer

Figure 3.2 shows the simplified diagram of the components shown in Figure 3.1. The arrows in the figure describe the power transfer between the components. A bi-directional arrow represents that the component can both act as a generation as well as a load.

Every component is considered to be 3 phase connected. Assuming constant 3 phase voltage at the POC to be $V_n = 400V$, the phase current can be calculated by Equation 3.1.

$$I_{ph}(t) = \frac{P_{grid}(t)}{\sqrt{3} \cdot V_n} \tag{3.1}$$

The electrical grid requires the grid current to stay within the threshold current of 25 A [33]. This is achieved with help of a fuse. The Energy Meter (EM) keeps account of the energy transfer to and from the electricity grid.

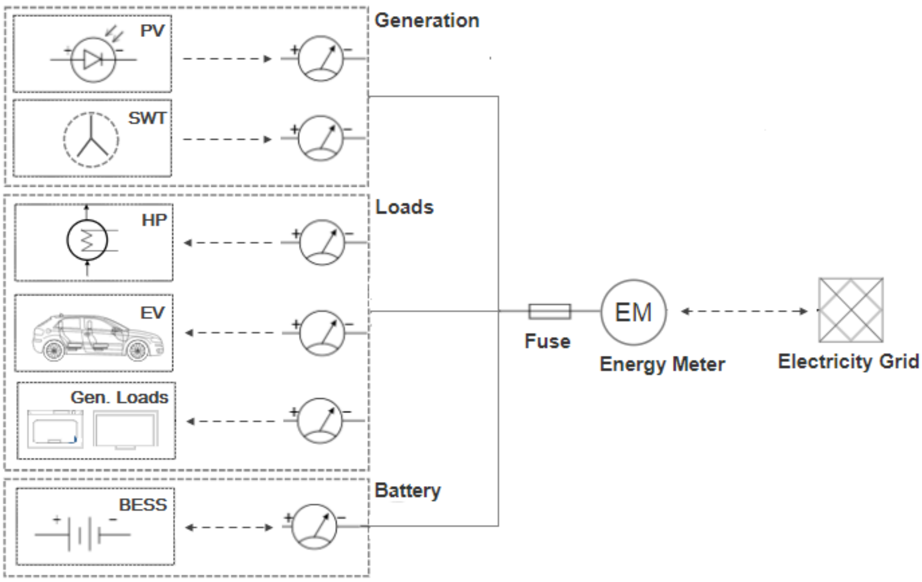

Figure 3.2: General powerflow directions

The EMS proposed in the next chapter aims to regulate the optimal power flows between these components in order to lower the overall electricity bill by utilizing a BESS.

3.1.1 Small Wind Turbine

A performance model for the study of a SWT suitable for EMS studies is described in [84], [85], [86].

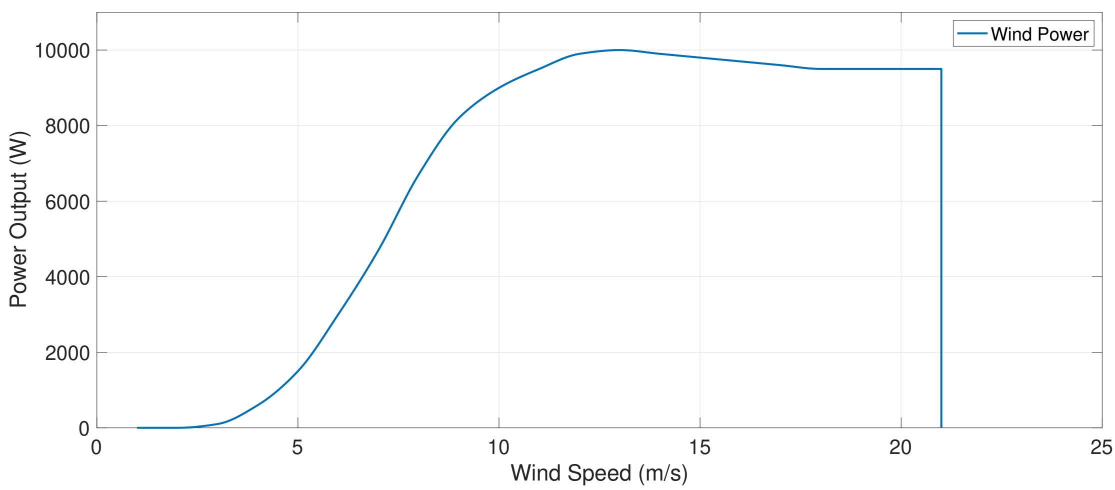

Figure 3.3: Power Curve of 10 kW Osiris wind turbine [86]

In this thesis, the power curve for the SWT used in the EMS is a look-up table that relates the wind speed to the power production of the wind turbine as provided in the manufacturer's data sheet. Power curves typically involves the effects of all the intrinsic components and overall component efficiencies. The power curve from the manufacturer Osiris Energy for 10 kW SWT (shown in Figure 3.3) is considered for this study [86]. This WT is certified for the Danish market [87].

3.1.2 Photovoltaic Cells

Photovoltaic cells facilitate the conversion of Solar Irradiance (G) to conventional electrical energy through Photovoltaic effect [88]. It is important to associate the electrical energy from the PV cells to the sunlight. The available sunlight is thus quantified in terms of G. It describes the power density and is measured in kW/m^2 [88].

According to the National Survey report of PV panel applications in Denmark, most of the residential or roof-top PV installations are 6 kW or smaller to benefit from the net metering scheme [10], [89], [90]. Thus, the data sheet of an LG Solar PV panel of $375W$ [91] is used for modelling the PV panels meaning that 16 of them is needed for the desired 6 kW capacity. The weather data for Solar Irradiation, Wind Speed and Ambient Temperature for a whole year (2013) was fetched from the weather station at Aalborg University [40] (Appendix A).

3.1.3 Heat Pump

The green transition requires all the energy to come from fossil-free sources. In 2020, 28% of all the global electricity demand is fulfilled through renewable energy [92]. However, the next important step towards green transition requires to use electricity from RES to fulfill the transport demands (EVs) and heat demands (HPs) [21]. Thus, it is important to include HPs in the modeling of the system.

The overall heat demand refers to the hot water demand and the heating required for maintaining desired temperature inside the house. According to a 2020 survey, the average size of a detached house in Denmark is $152m^2$ [93]. Considering the availability of RES and the sizing of the house, the HP size of 12 kW is considered sufficient.

The Coefficient of Performance (COP) of a heat pump is used to convert the heat demand of the household to an electrical demand. This relation can be represented by Equation 3.2, where $P_h(t)$ and $P_e(t)$ are the heat output and electrical input power respectively at time t and $COP(T_a)$ is the COP of the residential heat pump and defined by Figure 3.4 [21].

$$P_h(t) = COP(T_a) \cdot P_e(t) \tag{3.2}$$

In this thesis, year-long thermal demand for an average (detached) Danish household is obtained (see Figure A.5). The HP 'Aquarea H' (12 kW) from 'Panasonic' is used as a component [94]. The COP of the HP is given for 3 different ambient temperatures in the datasheet.

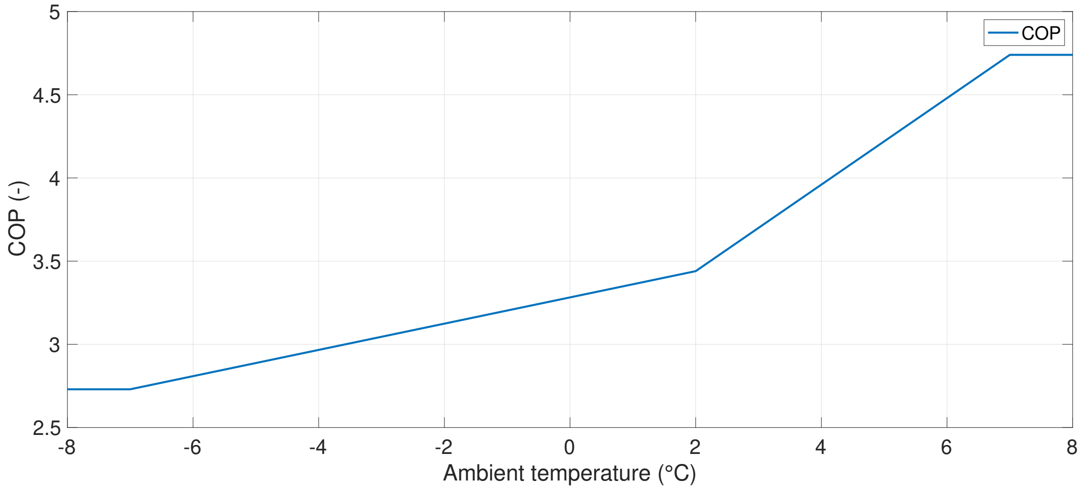

Figure 3.4: COP values of HP as a function of ambient temperature

Interpolating between those points the HP's COP can be determined at any ambient temperature. Outside of the defined curve COP is kept constant at the last known value.

3.1.4 Battery Energy Storage System

BESS is one of the most important component of the EMS. In this thesis, the BESS is modelled with RC - Equivalent Circuit Model [95], [96]. This model establishes the relationship between inputs such as current, temperature or SOC with the terminal voltage of the battery [97].

In this thesis, Lithium Iron Phosphate ($LiFePO_4$) batteries are considered from 'BYD' manufacturer as it is a well known producer of rechargeable batteries [98]. Three different battery sizes namely 6.4 kW, 10.24 kW and 11.52 kW were experimented on, to compare the impact of battery sizes on the end of the year cost and overall performance of EMS. The brief details of these batteries are shown in Table 3.1. It is also important to account for the degradation cost of the battery caused due to repeated charging and discharging, Section 4.2.2 explains the topic in further details.

Table 3.1: Battery Configuration and Prices

Configuration (No. of modules)	**Capacity** (kWh)	**Price** (kDKK)
5	6.4	27
8	10.24	39
9	11.52	43,5

3.1.5 Electric Vehicle

The electrical demand of EVs depend on the driving behaviour of the owner. Danish National Travel Survey statistically analyzes the driving behaviour of car owners based on 110,000 interviews conducted in Denmark over the last 10 years [99]. This data describes the general driving behaviour of people in Denmark who own four wheeled vehicles including the daily distances they travel as well as the arrival and departure times of these vehicles from the house.

Table 3.2: Parameters for Electric Vehicles [100]

Name	**Capacity** (kWh)	**Range** (km)	**Efficiency** (kWh/km)
Hyundai Kona	64	400	0.16
Nissan Leaf	36	220	0.164
Tesla Model 3	50	335	0.149
Audi e-tron S 55 quattro	86.5	320	0.27

Table 3.2 refers to four selected EVs to be studied as study cases in this thesis. The EVs are chosen to depict the effects of Battery Capacity (C_{EV}) and efficiencies for the different EVs. This thesis calculates the SOC of the EV battery (SOC^{EV}) from the distance travelled by the car (x) and the efficiency of the battery (c). The SOC of the EV battery at the time of arrival is given by Equation 3.3

$$SOC^{EV}_{arrive} = \frac{C_{EV} - c \cdot x}{C_{EV}} \tag{3.3}$$

The average daily travelled distance using all kinds of transport in Denmark is 39.5 km. Whereas, the average driving distance of a car is 45 km [101]. According to the Danish national survey, car users usually drive less during weekends than on weekdays [102].

In this thesis, EV owner is considered to be residing in a rural area in Denmark. Thus a normal distribution of daily distance travelled by the car is assumed, with mean 80 km and standard deviation of 5 km.

The residential EV charging stations in a typical Danish household use 11 kW three phase charging (or 3.7 kW single phase) [102]. Different charging patterns are used for EV charging. The most straight forward charging method is to plug the EV into the charging socket upon arrival and charge it until its battery is full. According to a study performed by the National Travel Surveys of Nordic Countries [102], a charging behaviour on weekdays and weekends in Denmark would look like Table 3.3. Typical leaving and arrival times of EV are considered.

Table 3.3: Driving behaviour of car owners [102]

	Departure time	**Arrival time**
Weekdays	7 am	6 pm ± 3 hours
Weekends	9 am	7 pm ± 4 hours

This behaviour is considered for the base case study in section 3.2. The EV is arriving at the time defined in Table 3.3 and immediately starts charging until is fully charged. However, this behaviour would probably put higher stress on the grid (charging is close to load peak) and shifting it for lower price hours could also provide financial benefits for the prosumer.

3.2 Base Case

In this section a scenario is proposed without any EMS or BESS. The SWT, PV, HP, EV and electrical loads are the active components. The excess energy from the RES is sold to the grid. The loads (electrical, thermal or EV) are fulfilled with RES and power from the grid. Grid power P_{grid} can be calculated as the sum of all power flows instantaneously, by Equation 3.4.

$$P_{grid} = P_{load} + P_{HP} + P_{EV} - P_{PV} - P_{SWT} \tag{3.4}$$

The electricity cost is obtained as a result of the power traded with the grid. The dynamic grid prices are fetched from the Nordpool for an entire year (2018) (See Appendix Figure A.1).

An analysis was performed for an entire year (the year of 2018). However, the power flows of the household for two 24 hour periods are shown in the case studies below. This is necessary to clearly see the charging period of EV and other power flows. The data is available for every hour, meaning 8760 data points for the examined year. The electrical load demand, produced PV and wind power and the HP electrical demand for the whole year can be found in Appendix A.

3.2.1 Base Case A: Winter day

A 24 hour period (from 09:00 1^{st} January, 2018 to 09:00 2^{nd} January, 2018) is taken under consideration to capture the power profiles of the household. The general parameters regarding the distance travelled by the EV, arrival and departure time of the EV etc. are listed in Table 3.4.

Figure 3.5 shows the active power flows during the 24 hour period. Tesla Model 3 Standard Plus is considered as EV (see Table 3.2 for ratings) for this demonstration, but the results for the other EVs can be found in table 3.6. Negative grid power (Purple line) means that the power is sold to the grid and positive grid power represents the power bought from the grid. In the beginning of the day, the SWT power fulfills the load and the excess power is sold to the grid.

Table 3.4: Base Case A: General Parameters

Parameter	Value
Day	Monday
Date	January $1^{st} - 2^{nd}$, 2018
Arrival time of EV	17:00 (Current day)
Total distance travelled by the EV	77 km
Departure time of EV	7:00 (Next Day)

Large peak in the load is observed around 17:00 due to the charging of the EV that occurs immediately after it arrives home.

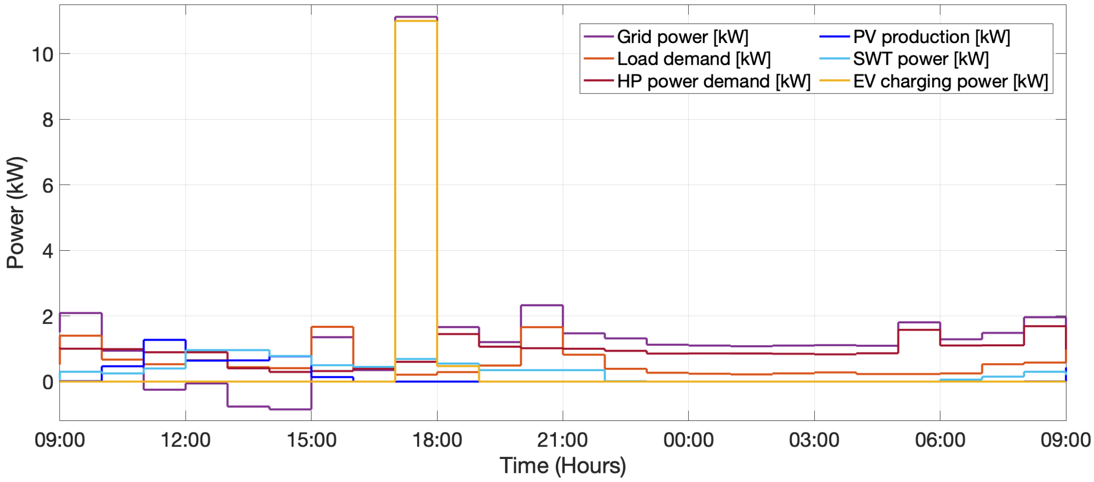

Figure 3.5: Base Case A: Winter Day Power Schedule, Tesla Model 3 SP

To depict the effect of using a different EV, the same conditions are applied to an another EV (Audi e-tron S 55). The resultant power profiles are shown in Figure 3.6.

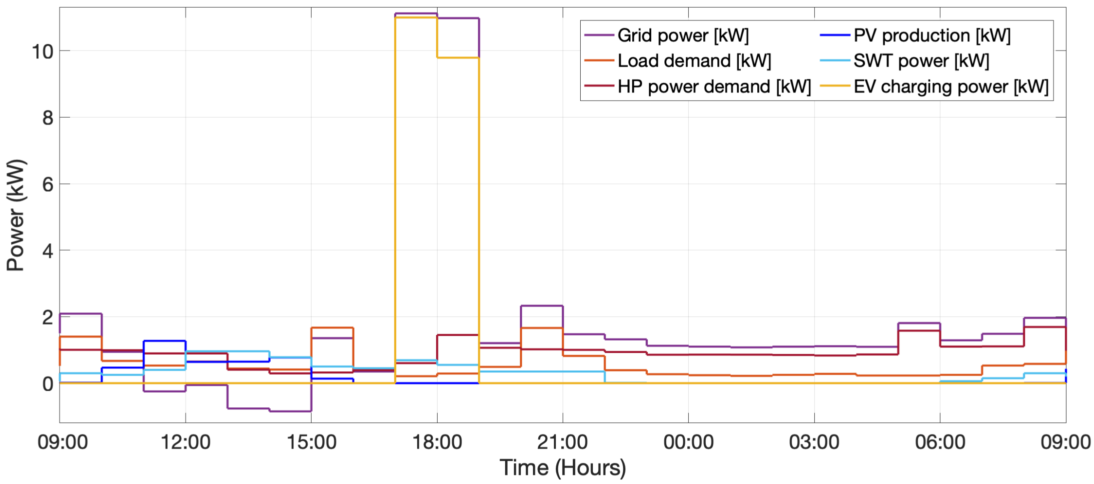

Figure 3.6: Base Case A: Winter Day Power Schedule, Audi e-tron S 55 quattro

This EV has a lower efficiency than the Tesla Model 3 SP, causing its battery to deplete more for the same distance travelled. Figure 3.6 shows that this EV takes more time and power to charge than the Tesla Model 3 SP.

3.2.2 Base Case B: Summer day

Another interesting case is taken into consideration to show the behaviour of these system components on a sunny day for a 24 hour period (from 09:00 5^{th} July, 2018 to 09:00 6^{th} July, 2018). Hyundai Kona is considered as an EV and its arrival time and distance travelled are listed in Table 3.5.

Table 3.5: Base Case B: General Parameters

Parameter	Value
Day	Sunday
Date	July $5^{th} - 6^{th}$,2018
Arrival time of EV	16:00 (Current day)
Total distance travelled by the EV	80 km
Departure time of EV	7:00 (Next Day)

Figure 3.7 shows the active power profiles obtained for this 24 hour period. There is a lot of PV production and wind power available during the day. The excess power from these RES is sold to the grid. The EV is charged at 16:00 as soon as it arrives.

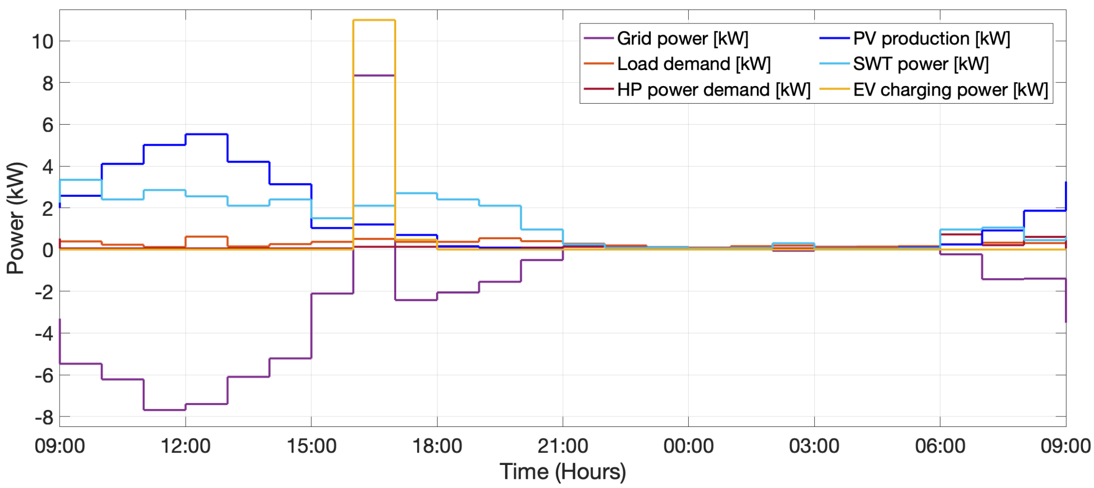

Figure 3.7: Base Case B: Summer Day Power Schedule, Hyundai Kona

3.2.3 Results

Table 3.6 shows the end of the year electricity prices for the different EVs used in the base case. The efficiencies (kWh/km) play a major role in the electricity prices. Although, a higher battery capacity for EV is desired for a higher travelling range it is also important to consider the efficiency of the EV in order to achieve lower electricity cost.

Table 3.6: Yearly Costs for the base case

Name	**Capacity** (kWh)	**Efficiency** (kWh/km)	**Electricity Cost** (DKK/year)
Hyundai Kona	64	0.16	7733.0
Nissan Leaf	36	0.164	7890.0
Tesla Model 3	50	0.149	7300.0
Audi e-tron S 55 quattro	86.5	0.27	12620.0

To see the stress put on the grid, the current demand of the house is calculated for the whole year according to Equation 3.1. The peak current drawn from the grid (I_{grid}) is 21.25 A for the whole year for Tesla Model 3 SP. These base cases will serve as a comparison for the scenarios utilizing EMS in Chapter 4. Scheduling the EV to lower priced hours, as well as installing and scheduling the BESS are expected to reduce electricity cost significantly.

3.3 Summary

A typical prosumer living in the rural areas of Denmark is described in this chapter. Defining the system components and the base case scenarios are inevitable steps of any efficient EMS design. As shown in Chapter 1, EVs are becoming more common. This poses a challenge for the low voltage grid as bigger amounts of cars are connected to the network at approximately the same time. Figures 3.5, 3.6 and 3.7 are clearly showing the peak effect of a single EV in a single household. To tackle this challenge on the smart prosumer's level, BESS and proper EMS has to be proposed. In the next chapter, DP based EMS will be described and applied to the same system.

4 | Optimization of EMS

The concept of EMS was introduced in chapter 1 as well its challenges. The core of every functioning EMS is its optimization algorithm. This thesis utilizes Dynamic Programming (DP) for the proposed EMS based on the literature review in chapter 2. In the following sections, the concept of DP is briefly introduced and explained by a simple example. The application of DP for the system described in chapter 3 is presented along with he objective function of the optimization and the considered constraints.

4.1 Dynamic Programming

DP was developed to solve a variety of multi-stage decision processes. Decision processes are processes when one needs to take a decision at certain points in time of the process which will eventually alter the result of it. Any system can be described with a set of quantities. In DP these quantities are called state variables [66]. The decisions mentioned before are actions that can modify the states of the system. Points in time when decisions can be made are called stages. Decisions can be defined as transitions between adjacent stages or the change in state variables. More precisely, the choice of transition is equivalent with the decision. Thus, decisions break down the whole process into sub-problems. If optimums could be found for the sub-problems, an overall optimum could be achieved [66]. Due to its structure, DP proves to be extremely efficient for solving scheduling problems. The full mathematical description of the method can be found in the Richard Ernest Bellman's book [66], but the basic principles will be explained in the next paragraphs.

In order to solve an optimization problem with DP, first the system has to be described with state variables. Then the process has to be divided into stages where the decisions take place. There are several possible ways to go through a process (depending on the decisions taken at each stage). A way or path is called policy. The purpose of the process is to minimize or maximize a function of the system states (objective function or cost function) at the final stage. A policy which yields the minimum/maximum objective function at the final stage is called an optimal policy [66]. Calculating the objective function for every feasible policy and then choosing the one with the minimum/maximum value would be a possible solution for the problem. However, that procedure would require immense computational power for even a moderate number of state variables or stages. Utilizing DP, the dimensions of the original decision process can be reduced to the decision problem occurring at any stage.

DP can only be applied when the problem has an optimal substructure [103], meaning that an optimal solution can be constructed from optimal solutions of its sub-problems. It focuses on the stage transitions. Solving every individual decision optimally leads to an optimal policy for the whole process. As the preceding decisions (states in previous stages) have an influence on the future ones, finding optimum for sub-problems is not so straight forward. Starting from the initial stage with an initial state the next stage's optimum for every state is going to be cost of transitioning to that certain state. However, moving to the next stage, every state is going to have an optimal predecessor state (in the previous stage). Moving through the optimal predecessor state(s) will provide an optimal cost function result for states in the next stage. In other words, an optimal policy for each state in every stage can be found in each stage transition. The optimum policy is only dependent on the transition of the current adjacent stages and the optimum policy of the state from which the transition started.

Solving these sub-problems recursively provides optimum policies for every state in the last stage [66]. Moreover, it will save the sub-optimums at every stage for every state. By fixing the state (desired state of the system at the end of the process) in the last stage, an optimal policy for the whole process is obtained. To further understand the procedure a numerical example is explained in the next section

4.2 Dynamic Programming: An example

Figure 4.1 illustrates a simple example with a graph that shows distances (cost of transition) between the nodes with dashed lines. Distance between two connected states are shown with a number on the dashed line, it can be interpreted as the cost of that particular state transition. The aim here is to reach the final node **J** from the initial node **A** with the shortest possible distance, i.e. cost. The system has 5 stages and states are represented by letters from **A** to **J**.

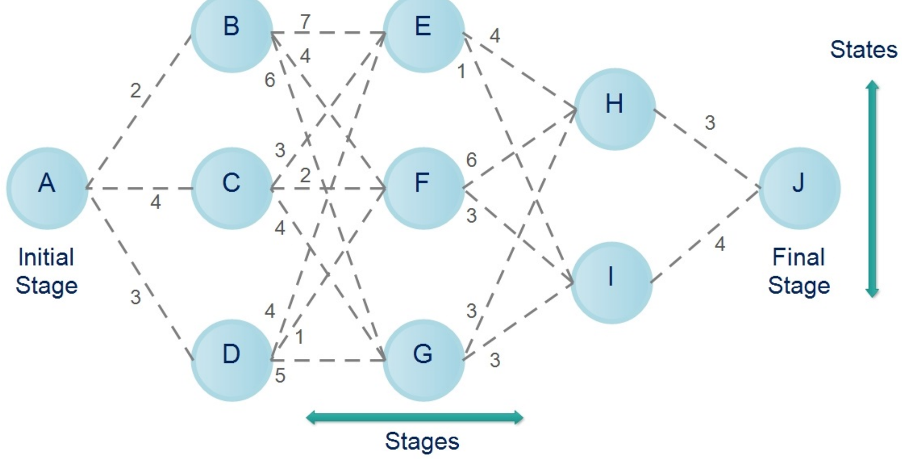

Figure 4.1: Example of Dynamic Programming using Bellman's graph

Applying a naive greedy approach to this problem, decisions are always made by choosing the next state in the next stage which requires the minimum transition cost (distance). Starting from stage **A** to stage **B** (with a cost of 2). Then the transition from state **B** to state **F** has the shortest path (cost of 4). Repeating the same process until **J** the final cost is $2 + 4 + 3 + 4 = 13$.

In contrast DP solves sub-problems, saves their optimum solutions then constructs the optimum for the global problem. These sub-problems overlap and are nested into each other. The original problem could be broken down into two sub-problems. Firstly, how to get to the $4th$ stage with optimum cost. Secondly, what is the minimum cost to transition from stage 4 to stage 5. The first sub-problem again, could be broken down into another 2 sub-sub-problems. How to get to stage 3 with optimal cost and how to transfer from stage 3 to 4 with minimum cost. If, one can solve these sub-problems recursively, the overall problem would be solved at the last step.

Starting DP with the first transition, optimum cost are found for states **A**, **B** and **C** in stage 2. Since its the first transition and the initial stage has only one state, every state's optimum is the transition cost from the previous stage. Moving to the next stage and sub-problem, optimum costs (and policies) have to be found for state **E**, **F** and **G** in stage 3. The following 3 equations show the process:

$$CF_o(E) = min\{7 + CF_o(B), 3 + CF_o(C), 4 + CF_o(D)\} = min\{9, 7, 7\} = 7$$

$$CF_o(F) = min\{4 + CF_o(B), 2 + CF_o(C), 1 + CF_o(D)\} = min\{6, 6, 4\} = 4$$

$$CF_o(G) = min\{6 + CF_o(B), 4 + CF_o(C), 5 + CF_o(D)\} = min\{8, 8, 8\} = 8$$

Where CF refers to the cost function evaluated at the given state (with given policy), while the subscript "o" denotes the optimum value of cost function at that state. Same process for the next sub-problem:

$$CF_o(H) = min\{4 + CF_o(E), 6 + CF_o(F), 3 + CF_o(G)\} = min\{11, 10, 11\} = 10$$

$$CF_o(I) = min\{1 + CF_o(E), 3 + CF_o(F), 3 + CF_o(G)\} = min\{8, 7, 11\} = 7$$

Finally, the global optimum will be yielded by the last sub-problem:

$$CF_o(J) = min\{3 + CF_o(H), 4 + CF_o(I)\} = min\{13, 11\} = 11$$

So the minimum cost (or distance) to get from **A** to **J** is 11. It is clear that the greedy method does not yield in the optimum solution. Moreover, it is shown that as previously mentioned, the dimension of the optimization problem is reduced to the dimension of the sub-problem of a single stage transition. By saving the optimum predecessors for every state in every stage, the solution would also provide the optimal policy (or route) for state **J** in the final stage. Table 4.1 depicts the optimal predecessors for every state.

Table 4.1: Optimal predecessors for states

State	Optimal Predecessor
A	-
B	A
C	A
D	A
E	C, D
F	D
G	B, C, D
H	F
I	F
J	I

By selecting any state from the table, going backwards through optimum predecessors, the optimal policy can be obtained. For **J**, the optimal policy is: **J** $\Leftarrow$ **I** $\Leftarrow$ **F** $\Leftarrow$ **D** $\Leftarrow$ **A**.

4.2.1 Implementation of Dynamic Programming in EMS

In order to apply DP for the system described in chapter 3, states and stages need to be defined.

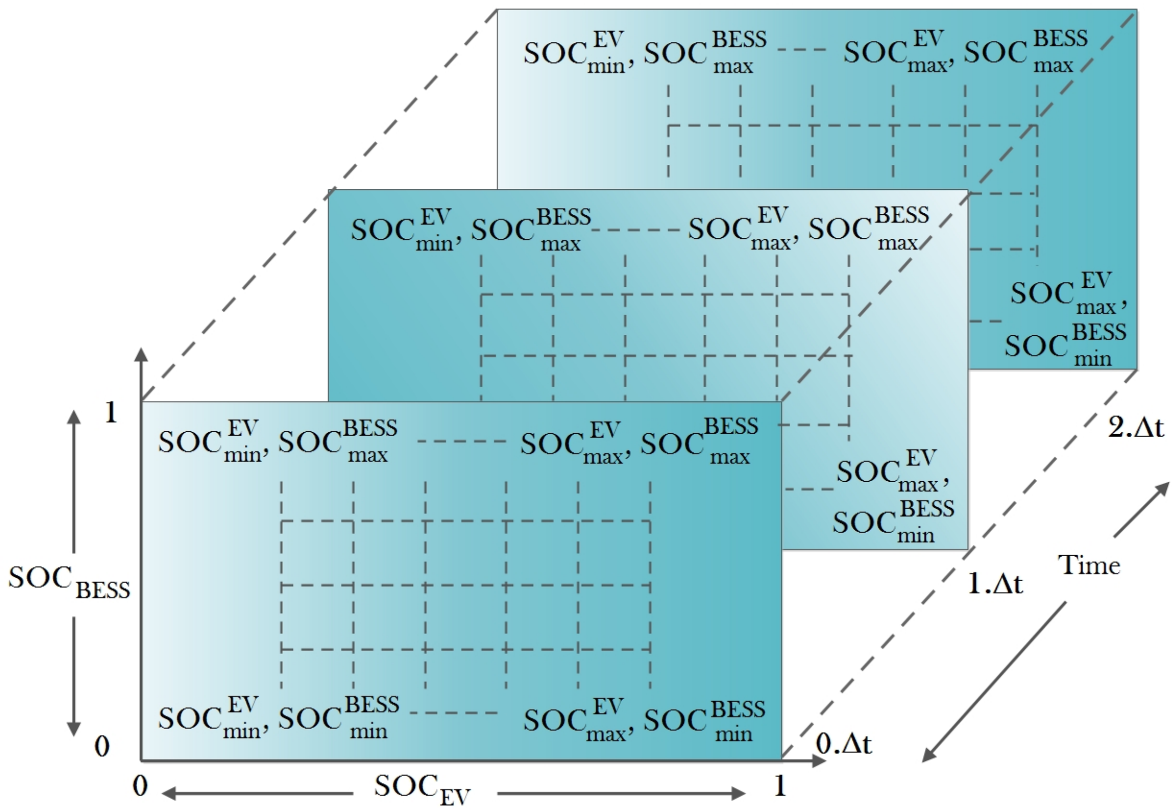

Figure 4.2: System's State

For the considered system, two state variables have been selected. One being the SOC level of the

BESS. The other one is the SOC level of the EV. This way, the EMS can select the desired SOC level of BESS and EV at any stage and set the power commands accordingly. Figure 4.2 shows the states and stages of the system.

A stage can be represented by a plane, where the row number defines the SOC level of the BESS while the column number defines the SOC level of the EV. A stage transition is moving from one point in one plane to one point in the next stage. The discrete resolution of time (Δt) and SOC (δSOC^{BESS}) can be set to match the considered optimization horizon. For a given δSOC^{BESS} resolution (SOC difference between adjacent states) the number of states in any stage regarding SOC^{BESS} is:

$$N^{BESS} = \frac{SOC^{BESS}_{max} - SOC^{BESS}_{min}}{\delta SOC^{BESS}} \tag{4.1}$$

where SOC^{BESS}_{max} and SOC^{BESS}_{min} constrain the maximum and minimum SOC of the battery and can be set by the user. Regarding the SOC states of EV, the number of states is more complicated. The availability of EV for charging is dependant on the driving habits of the inhabitants. Considering the same habits as described in section 3.1.5, EV is available between the arrival time of the current day and the leaving time of the next day.

Taking this and the EV charging constraint (Equation 4.5) into account the number of SOC^{EV} states has to be recalculated every time the EV arrives at the house. The SOC^{EV} states can be calculated based on the time resolution of DP and the SOC^{EV} at the time of arrival:

$$N^{EV} = (1 - SOC^{EV}_{arrive})/\delta SOC^{EV} + 2 \tag{4.2}$$

Where "/" refers to integer division. The "+2" term is needed to account for the minimum state being: SOC^{EV}_{arrive} and the maximum state being 1. Then δSOC^{EV} is defined by Equation 4.3:

$$\delta SOC^{EV} = \frac{P^{EV}_{charge} \times \Delta t}{C^{EV}} \tag{4.3}$$

P^{EV}_{charge} stands for the nominal charging power of the EV. Notice that δSOC^{EV} is also the biggest possible SOC change of the EV during stage transition, i.e $\delta SOC^{EV} = \Delta SOC^{EV}_{max}$. The objective of the proposed EMS is to find the optimal policy of ΔSOC^{BESS} and ΔSOC^{EV} transitions that would minimize the CF cost function (Equation 4.10) at the last stage, while fulfilling the constraints.

Figure 4.3 shows the possible powerflow directions between assests as well as the sign conventions for BESS and grid power.

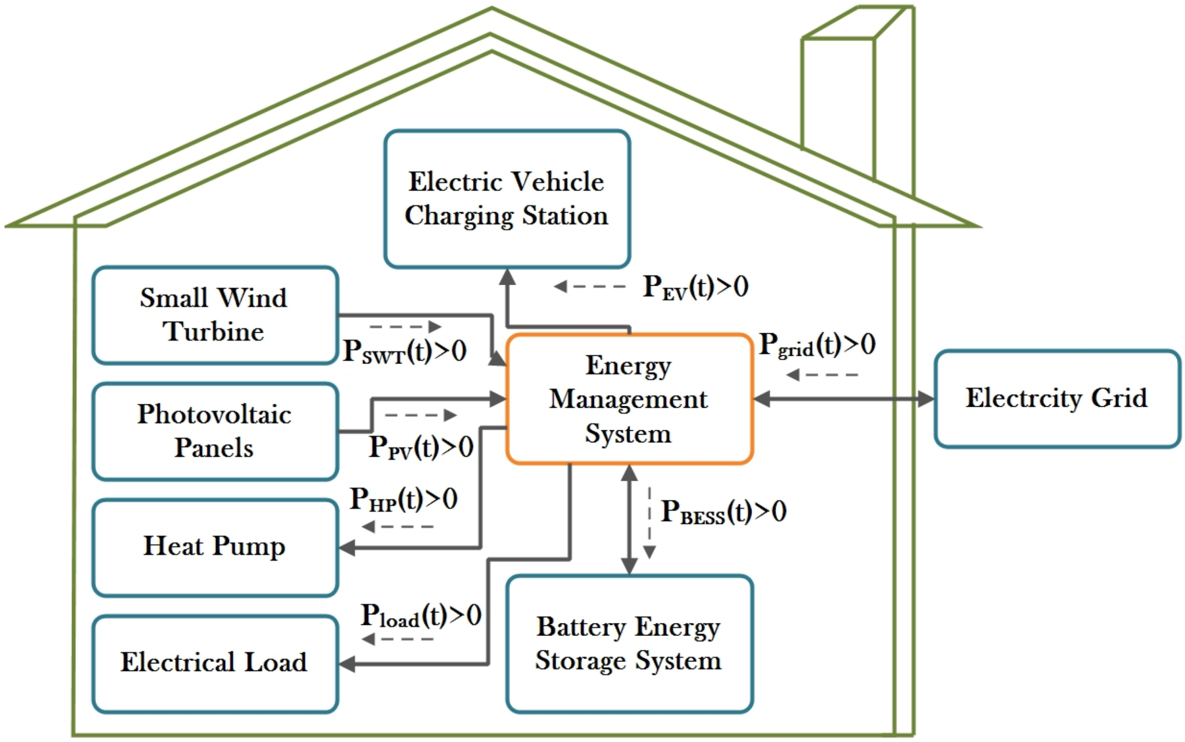

Figure 4.3: Sign Conventions for the power flows

Here, t is the discretized time, which defines the stages (S). For the BESS, $P_{bat} \leq 0$ means the battery is discharging and can be represented as a power source. On the contrary,$P_{bat} > 0$ means the battery is charging and acting as a load. As for the grid power, positive values stand for power being taken from the grid, while negative ones stand for pushing the power to the grid. Based on the sign conventions the following constraints has to be fulfilled at every stage and for every stage transition:

Power balance:

$$P_{Grid}(t) = P_{Bat}(t) + P_{Load}(t) - P_{PV}(t) + P_{HP}(t) + P_{EV}(t) - P_{SWT}(t) \tag{4.4}$$

The instantaneous power balance at every stage has to be fulfilled.

EV Power:

$$P_{EV}(t) = \begin{cases} 11 \text{ [kw]}, & \text{if EV is being charged} \\ 0, & \text{otherwise} \end{cases} \tag{4.5}$$

EV power as mentioned in 3.1.5 can only be the nominal charging power during charging and 0 when the car is not being charged.

BESS Power:

$$P_{Bat}^{min} \leq P_{Bat}(t) \leq P_{Bat}^{max} \tag{4.6}$$

The battery power is limited to ensure its safe and efficient operation. The limits are defined in the datasheet but also can be further tightened by the user [98].

BESS SOC limits:

$$SOC^{min} \leq SOC(t) \leq SOC^{max} \tag{4.7}$$

BESS has to operate within these SOC limits that can be set by the user. More conservative limits can extend the battery life, but also result in lesser flexibility for the prosumer.

EV SOC limits:

$$SOC_{EV}(t) = \begin{cases} SOC_{arrive}^{EV} \leq SOC_{EV}(t) \leq 1, & \text{if EV is home} \\ 1, & \text{otherwise} \end{cases} \tag{4.8}$$

According to Equation 4.5 and Equation 4.3 SOC^{EV} can only occupy those specific SOC states while it is set as 1 while the EV is not present at the house.

Grid constraint:

$$I_{grid}(t) < 25 \text{ [A]} \tag{4.9}$$

The current drawn by the household can never violate this constraint, otherwise the over current protection will be tripped.

Objective Function:

Finally, the objective function to be minimized:

$$Min(CF) = Min\left(\sum_{S=0}^{T} CR(\Delta S) + CP(\Delta S)\right) \tag{4.10}$$

$CR(\Delta S)$ accounts for energy sold to the grid between stage S and $S+1$ and calculated by Equation 4.11. Correspondingly, CP accounts for purchased energy between adjacent stages and defined by Equation 4.10.

$$CR(\Delta S) = P_{grid}(\Delta S) \cdot FIT(\Delta S) \cdot \Delta t + Y_{bat}(\Delta S) \tag{4.11}$$

$$P_{grid} \leq 0$$

$$CP(\Delta S) = P_{grid}(\Delta S) \cdot GP(\Delta S) \cdot \Delta t + Y_{bat}(\Delta S) \tag{4.12}$$

$$P_{grid} > 0$$

Where ΔS denotes a stage transition from stage S to $S+1$. $GP(\Delta S)$ and $FIT(\Delta S)$ are the electricity price and FIT respectively, during the stage transition. Y_{bat} stands for the battery degradation cost for the same transition and Section 4.2.2 shows the details of its calculation.

Figure 4.4 shows the working of the proposed DP based optimization.

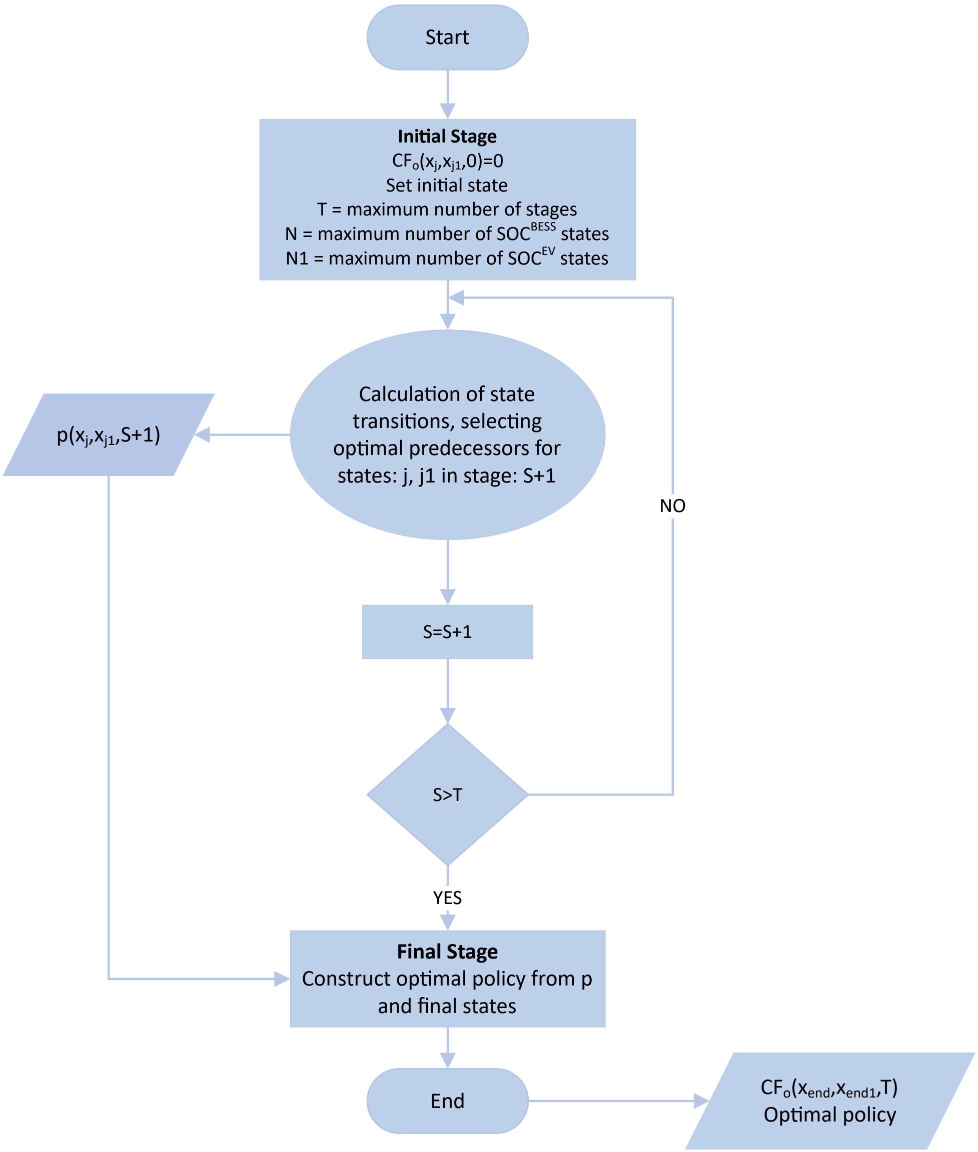

Figure 4.4: High level working of DP algorithm

It follows the same process as that discussed for the example in Section 4.2. DP calculates and selects optimal predecessors for every state in every stage and saves them in p.

Every iteration is a stage transition from S to $S + 1$. At the end of the process, selecting the last states in the last stage, optimal policy is constructed backwards from p. Figure 4.5 reveals how DP goes through every state transition.

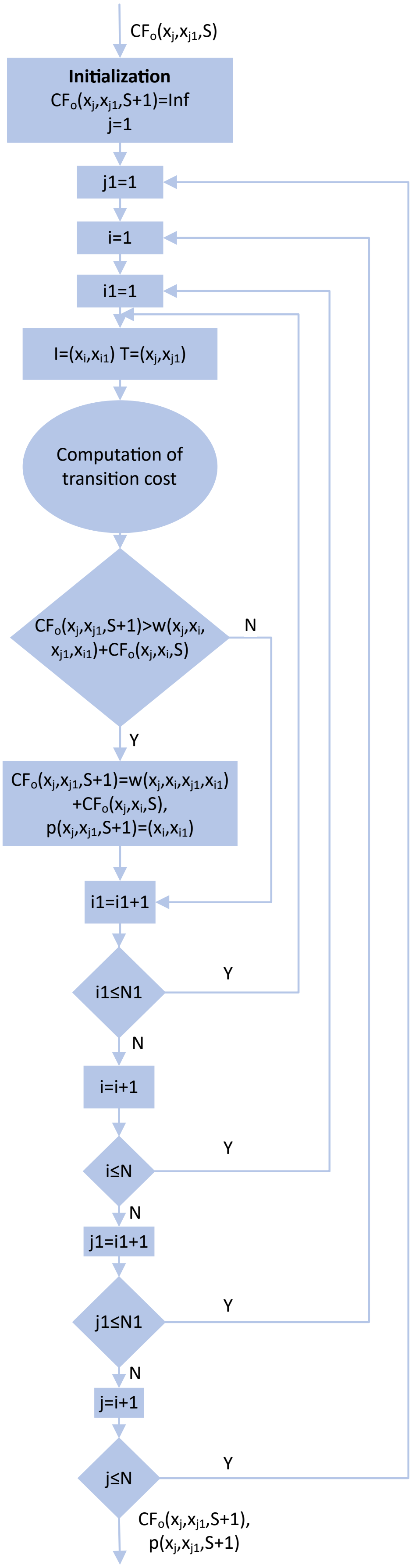

Figure 4.5: Selecting optimal predecessors

These loops go through every state transition possible between the two stages. First the system initializes every state's optimum cost for the next stage as 'Infinite'. The two states require 4 indexes to describe a stage transition. State "i" and "$i1$" are the states in stage S from where the transition starts and represent SOC values for BESS and EV respectively. Similarly, "j" and "$j1$" are the states where the transition ends in stage $S+1$ for BESS and EV SOC respectively.

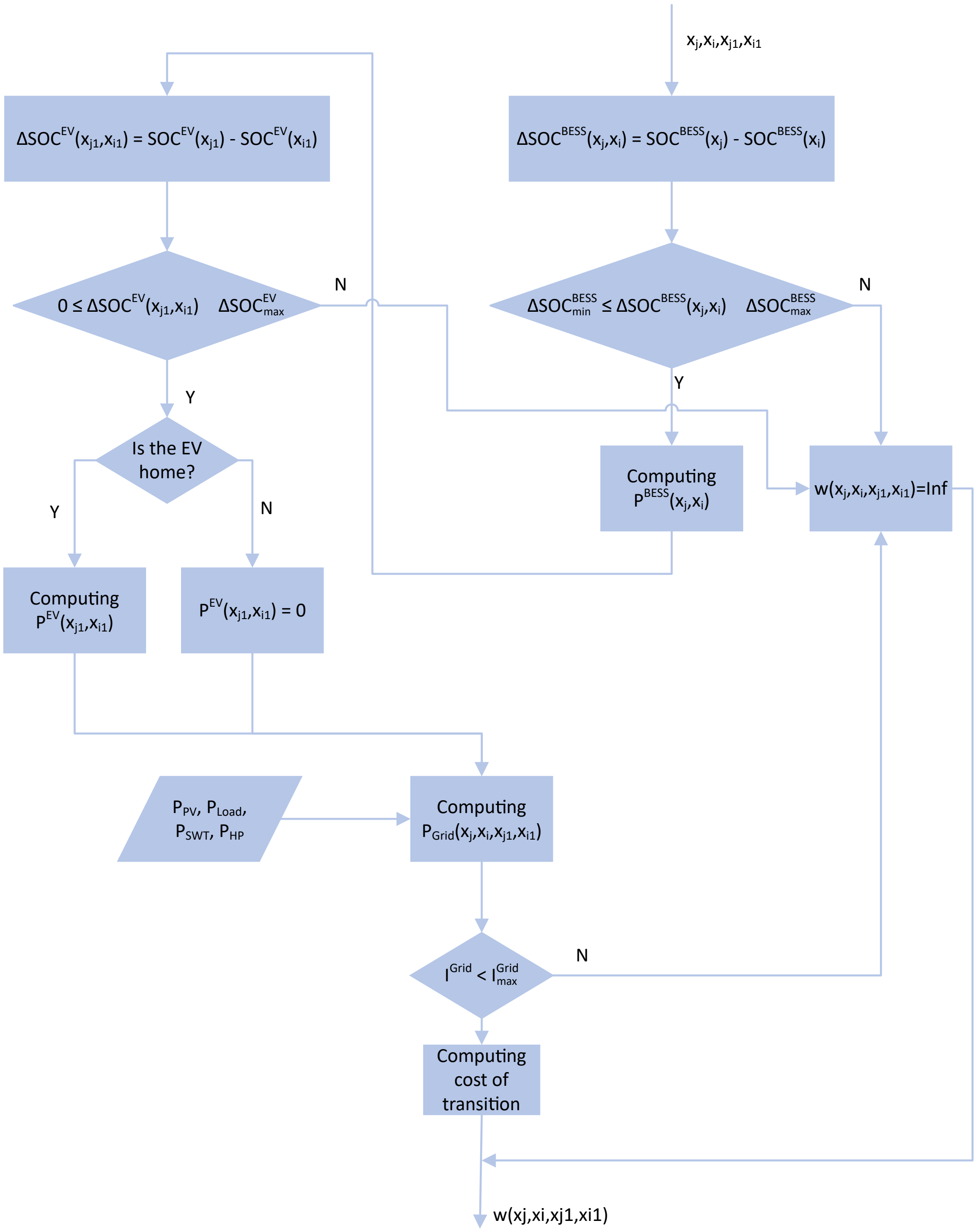

Figure 4.6: Calculating transition cost between states

As the algorithm looks for optimal predecessors for states, it goes through all values of "i" and "$i1$"

for every "j" and "$j1$" combination. Whenever the sum of transition cost plus the starting state's optimum cost is smaller then any previous value, the system saves it as the optimum. Simultaneously, it saves the previous states as optimal predecessors in "p". This way, all states in every stage will have an optimal policy.

Figure 4.6 presents the calculation of the transition cost ($w(x_j, x_i, x_{j1}, x_{i1})$) for any state transition. ΔSOC values for both BESS and EV can be calculated based on the starting and finishing states. Constraints for BESS (Equation 4.6) and EV power (Equation 4.5) can be transformed into ΔSOC constraints by taking into account Δt. Any transition that violates a constraint is associated with an 'Infinite' transition cost. After calculating the necessary P^{BESS} and P^{EV} for the given transition, the power balance (Equation 4.4) is used to determine P_{Grid}. Finally, the cost of transition is calculated by Equation 4.11 and 4.12 depending on the sign of P_{Grid}.

4.2.2 Battery degradation

It is important to account for the cost of battery usage during operation. Charging and discharging cycles shorten the lifetime of the BESS and that needs to be assessed. The actual cost of every $\Delta SOC^{BESS}(\Delta S)$ has to be considered for the optimal strategy. This cost is expressed as cost of battery degradation and added to the cost function in Equation 4.12 and 4.11.

Several literature studies the performance degradation of the batteries [104], [105]. The loss of battery capacity is often represented linear according to the depth of discharge of batteries [106], [107]. National Solar Energy Institute (INES) in France performed an analysis for the aging data obtained for 150 different batteries with different technologies [71], [105]. From their analysis, the linear aging coefficient (Z) for different battery technologies has been proposed. The aging coefficient relates the capacity fade for the battery to the total number of charging discharging cycles that it encounters. The value of Z for lithium-ion batteries is 1.7×10^{-4} [71].

The aging model presented in this section has to be modified to a certain extent to fit the DP application of the EMS. The detailed description of the model can be found in [106]. The degradation cost is considered for every stage transition and is only dependent on Z, the installation cost of the given battery (BiC) and the minimum State of Health (SOH) of the given battery.

As the degradation is considered linear, the cost of replacing the battery can be distributed along its lifetime. During each transition, a cost for the capacity loss of the battery can be calculated based on Z and the installation cost. Defining SOH_{min} as the state of health of the battery when the battery has to be replaced, transition cost as a function of ΔSOC^{BESS} can be calculated by the following equation:

$$Y_{bat}(\Delta S) = BiC \times \left(\frac{-Z \times |\Delta SOC^{BESS}(\Delta S)|}{1 - SOH_{min}} \right) \tag{4.13}$$

The SOH_{min} of 0.7 is considered for the purpose of this study meaning that the battery is considered unsuitable for its application once SOH crosses the threshold of 0.7 [104]. Using the installation costs from Table 3.1, a linear coefficient (BrC) is calculated for every battery and listed in Table 4.2.

Table 4.2: Battery degradation coefficients

Capacity (kWh)	**Price** (kDKK)	**BrC** (DKK)
6.4	27	1.529
10.24	39	2.22
11.52	43.5	2.466

Using the coefficient, degradation cost for a single stage transition:

$$Y_{bat}(\Delta S) = BrC \times |\Delta SOC^{BESS}(\Delta S)| \tag{4.14}$$

4.3 Case Studies

To test the efficiency of the proposed EMS on the system, the same year long analysis is conducted as in Section 3.2. Different parameters are varied such as BESS size, SOC limits, EV types, etc. To see the financial impact of the optimization, costs are compared at the end of the section. The detailed description of the power profiles used (for PV generation, SWT power, loads etc) and some examples of the resulting schedules are available in Appendix A. While the resulting detailed costs are available in Appendix B.

There are two study cases shown for the response of the DP based EMS. The two study cases are the same days as in the base case (Section 3.2). The reason is to help understand the differences between prosumers equipped with EMS + BESS and prosumers without these assets. Because the available data is hourly sampled, DP can take decision on EV and BESS usage every hour, meaning stages are defined as points in time which are exactly an hour away from each other.

The smallest BESS technology (6.4 kWh) is utilized for showcasing the two 24 hour period along with the 'Tesla Model 3 Standard Plus' as the considered EV (as according to the cost analysis performed in Appendix B, lowest costs were incurred for this EV). The parameters for the BESS considered in the following study cases are summarized in Table 4.3.

Table 4.3: Study Case A: BESS Parameters

Parameter	Value	Parameter	Value
Battery Size	6.4 kWh	SOC_{min}	0.2
δSOC	0.1	SOC_{max}	0.9
P_{Bat}^{max}	6.4 kW		

4.3.1 Study Case A: Winter Day

The first study case to observe the response of the DP based EMS is again the winter day (January 1^{st}, 2018). The conditions of the EV (distance travelled, arrival time at the house, SOC of the EV after arrival) are shown in Table 4.4.

Table 4.4: Study Case A: General Parameters

Parameter	Value
Day	Monday
Date	January $1^{st} - 2^{nd}$, 2018
EV used	Tesla Model 3 Standard Plus
Arrival time of EV	17:00 (Current day)
Total distance travelled by the EV	77 km
SOC of the EV after arrival	0.8075
Departure time of EV	7:00 (Next Day)

Figure 4.7 shows the optimal power schedule obtained from the EMS for the previously detailed 24 hour period in winter and the electricity prices during that period. The prices for this day are lower after mid-day (15:00, January 1^{st}) and post mid-night (after 01:00, January 2^{nd}).

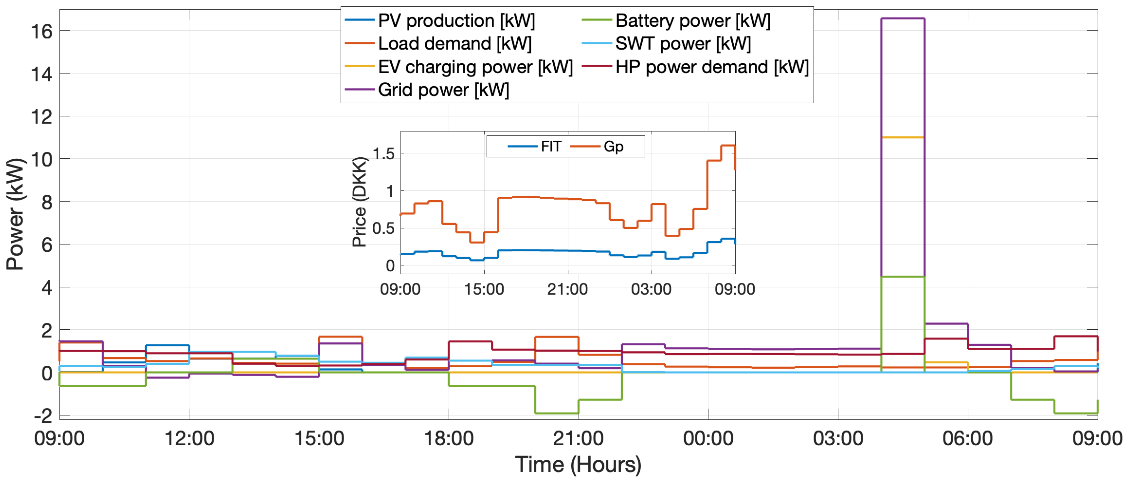

Figure 4.7: Study Case A: Winter Day Power Schedule

In accordance with the season, the HP and the load demands of the household (magenta line, red line) are higher than a typical summer day (as depicted in subsection 4.3.2) throughout the 24 hour period. RES production from PV and SWT (blue line, cyan line) are also minimal. When the grid prices are higher in the evening (16:00 - 22:00), the BESS discharges to avoid buying electricity from the grid.

The EV arrives at home at 17:00 in the evening. However, unlike the base case (Section 3.2.1), the EV is scheduled by the EMS to charge when the grid price is low (after mid-night). The BESS also charges after mid-night and discharges again in the morning hours to fulfil the HP and load demands when the grid prices increase.

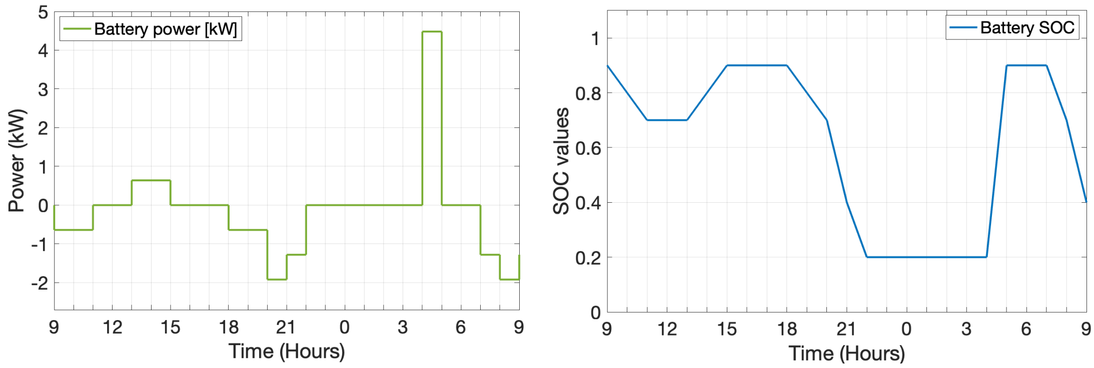

Figure 4.8: Study Case A: (a)Battery Power (b)Battery SOC

Figure 4.8 shows the BESS power and the corresponding SOC profile. As the grid prices are the most dominant factor in the optimization, EMS schedules both the EV and BESS charging to the same hour. While the grid constraint (Equation 4.9) ensures that the current stays below the limit, this behaviour could lead to problems during real time operation.

4.3.2 Study Case B: Summer Day

A summer day (July 5^{th}, 2018) is also considered to observe a different scenario. The conditions of the EV (distance travelled, arrival time at the house, SOC of the EV after arrival) are shown in Table 4.5.

Table 4.5: Study Case B: General parameters

Parameter	Value
Day	Sunday
Date	July $5^{th} - 6^{th}$,2018
EV used	Tesla Model 3 Standard Plus
Arrival time of EV	16:00 (Current day)
Total distance travelled by the EV	80 km
SOC of the EV after arrival	0.80
Departure time of EV	7:00 (Next Day)

Similarly to the previous Section, Figure 4.9 shows the optimal power schedule and the electricity prices for the considered period. PV and wind power production are plenty from 09:00 to 15.00 and also in the next morning, while load and HP is minimal during the whole period.

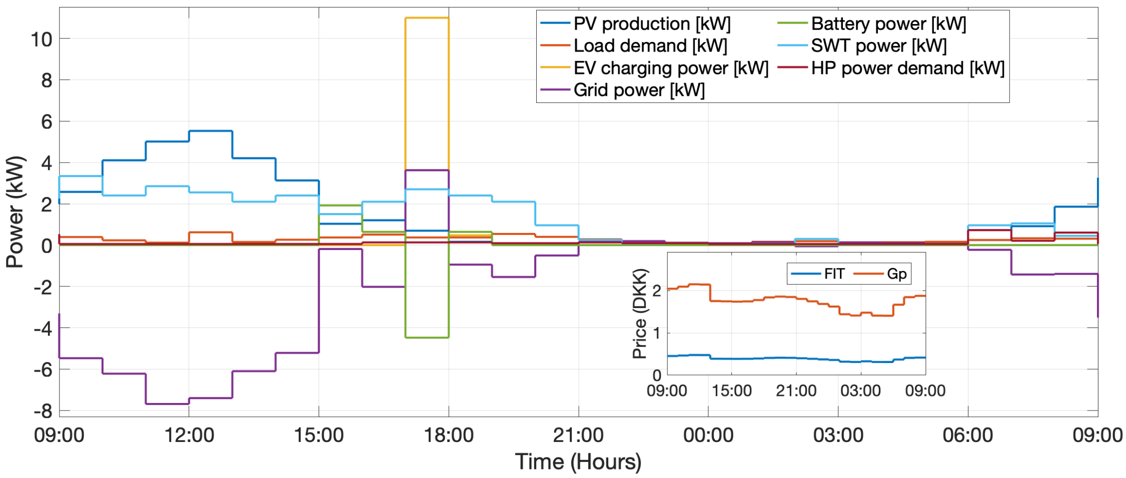

Figure 4.9: Study Case B: Summer Day Power Schedule

As the corresponding grid prices and FIT are higher during the day, the power from RES is sold to the grid. When the grid prices are lower around 15:00, the BESS charges (green line). The EV returns home at 16:00 and is scheduled to charge around 17:00 with BESS, RES and the grid power. Figure 4.10 shows the BESS power and the corresponding SOC profile.

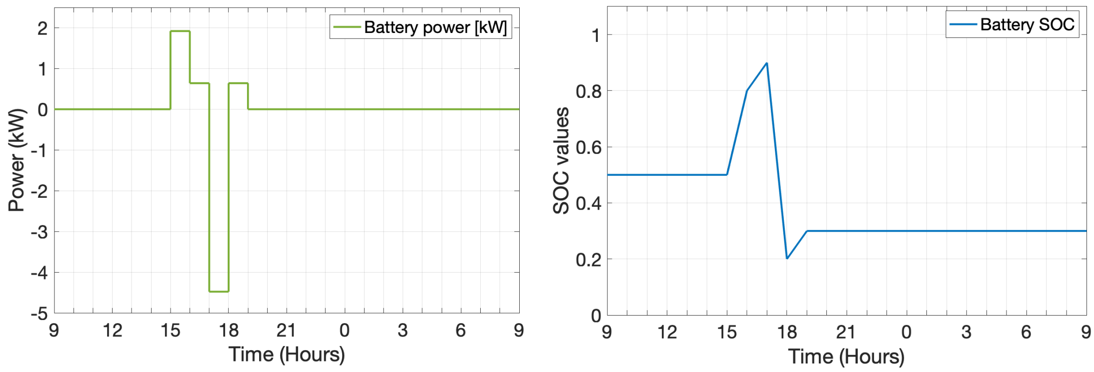

Figure 4.10: Study Case A: Summer Day Battery SOC

As RES production was sufficient for most of the time, BESS was mainly scheduled to help the EV charge. Moreover as only 24 hour is shown, power profiles before and after this period are also influencing the optimal schedule.

4.4 Conclusion of Scenarios

These particular days presented above only provide a glimpse of the working of the EMS. However, in order to see the true potential of the EMS both in terms of economical benefits and flexible component handling, the year long analysis has been conducted for various combinations of some components and operation parameters. Tests were varying the BESS size, EV type, grid current limit and permissible SOC range of BESS. δSOC has been arbitrary selected as 0.1. This can be reasoned by the time between stages. Since data points and decision making points are both hourly, finer resolution of SOC is not required. The problem of time and SOC resolution, along with the connection between them is discussed in a later chapter. Resulting grid costs, BESS degradation cost and overall costs were calculated and compared.

The degradation cost is the total BESS degradation cost incurred in DKK throughout the whole year (calculated according to Section 4.2.2). Grid cost refers to the price of the electricity exchanged with the grid and overall cost is the summation of the degradation cost and grid cost. In the following scenarios the grid current limit was kept at 25 [A] (keeping the constraint in Equation 4.9), to see the effect of lowering this value, a separate test was conducted and can be seen later in this section. The proposed EMS was subjected to four different EV types and different parameters such as BESS sizes and allowable BESS SOC range were varied. The exact costs as well as peak grid currents obtained from permutations of possible SOC ranges and BESS sizes are presented in Appendix B (Tables B.1, B.2, B.3 and B.4). The only difference among the four different types of EVs tested, is the efficiency of the EV (measured in kWh/km). Nevertheless, it has a visible impact on the final electricity cost (See Appendix B for more details). The effect of BESS parameters on the financial aspects and end of the year costs can be seen in Figure 4.11 featuring the 'Tesla Model 3 Standard Plus'.

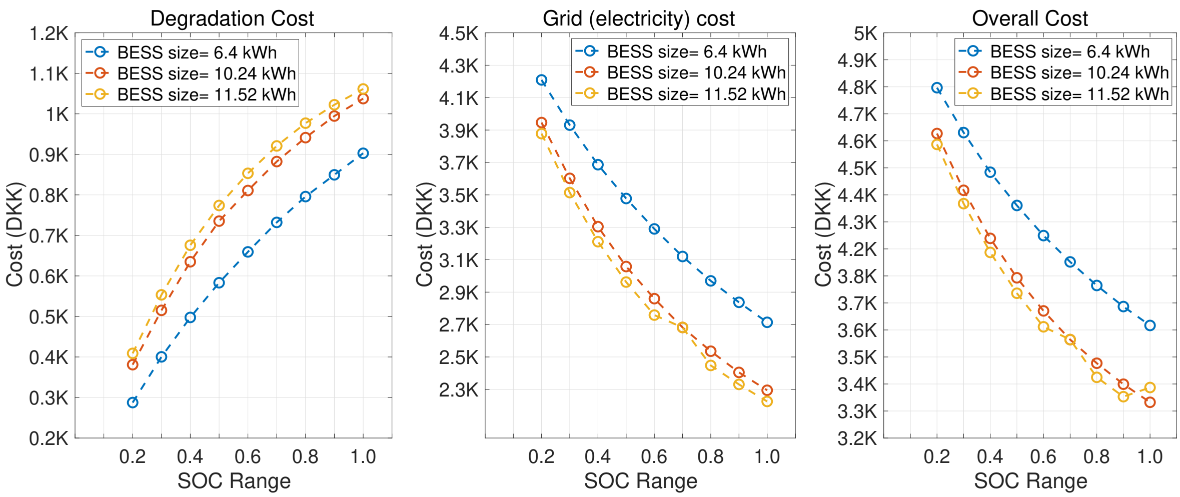

Figure 4.11: Cost comparison: Tesla Model 3 Standard Plus

'SOC Range' refers to the total available range compared to the nominal capacity of the specific battery. For instance, if the battery can take SOC levels between 0.9 and 0.2 (Equation 4.7), then its 'SOC Range' is 0.7.

As it can be expected, BESS degradation costs are lower for smaller BESS sizes. However, bigger BESS capacity brings bigger flexibility, thus reduced grid (electricity) cost. Utilizing a wider SOC range will further reduce grid cost and seems to out weigh the increased degradation costs. This trade off between the BESS degradation cost and the grid cost can be particularly observed for 11.52 kWh BESS size in Figure 4.11. As the SOC range is increased from 0.9 to 1, the overall cost for 0.9 is lower compared to the overall cost for the maximum SOC range of 1. As the overall cost gains are becoming less and less as the maximum SOC range is approached, it is up to the users if they would like to consider limiting BESS flexibility for potential preservation of its health.

To see how the EMS performs under different grid current limits, the I_{grid}^{max} from Equation 4.9 has been varied between 20 and 25 [A]. The results can be seen in Figure B.1 (Appendix B). All 3 BESS sizes has been tested with $SOC_{min} = 0.2$ and $SOC_{max} = 0.9$, while the considered EV was the 'Tesla Model 3 Standard Plus'. The results show that by limiting the grid current below 20 [A], the overall prices only rise with a 2-4 DKK the whole year. Given the lower grid current ensures higher safety margin, keeping the limit at 20 [A] is considered as the favourable option.

The main findings of the cost analysis shown in Appendix B (Tables B.1, B.2, B.3 and B.4) can be summarized as follows:

- The degradation cost is lower when BESS is operated for a narrower SOC range (SOC values ranging from 0.3-0.8) than when it is operated with wider ranges (SOC values ranging from 0-1).
- Operating BESS with wider SOC ranges (e.g. 0-1 or 0.2-0.9) reduces the grid cost, however, due to the increased BESS degradation costs, in some cases the overall cost can be higher.
- The BESS size also plays a significant role in the overall cost. Higher BESS size has higher installation cost and thus the degradation of its capacity can prove costly. Also, due to its bigger capacity, it provides greater flexibility to the system which results in lower grid costs.
- The EV capacities and efficiencies play a major role in determining the overall prices. The lower is the efficiency of the EV (measured in kWh/km) the more expensive it proves in terms of overall cost.
- The DP based EMS effectively limits the peak current drawn from the grid (I_{grid}) with negligible additional cost.

Table 4.6 shows the the overall cost of operating the household with EMS deployed and without it. The considered SOC range is $0.2 - 0.9$ which is a compromise between flexibility and preserving BESS.

Table 4.6: Cost of electrical energy for Base Case and overall cost for DP based EMS scheduling

EV	BESS Size (kWh)	Base Case	DP based EMS 6.4	10.24	11.52
Hyundai Kona	Price (DKK/year)	7733.0	4131.9	3845.6	3791.9
	Saving (%)	-	46.56	50.27	50.96
Nissan Leaf	Price (DKK/year)	7890.0	4236.3	3947.7	3894.1
	Saving (%)	-	46.30	49.96	50.64
Tesla Model 3 SP	Price (DKK/year)	7300.0	3851.9	3476.8	3564.3
	Saving (%)	-	47.23	52.37	51.17
Audi e-tron	Price (DKK/year)	12620.0	7399.6	7084.7	7027.6
	Saving (%)	-	41.3	43.86	44.31

Savings can be achieved up to 52 %, which underlines how effective DP based EMS can be. Using the most efficient EV (Tesla) without any EMS costs more than using the least efficient (Audi) EV, but with EMS deployed. Also, one actually saves more in long term (one year in this case) if battery of higher capacity is used.

4.5 Summary

The proposed DP based EMS has been proven to be effective and could achieve significant cost reductions. It can sufficiently comply with the grid constrains and ensures reliability by charging the EV to 100 % by the time its needed. Flexibility of the algorithm is one of the most important aspect when it comes to household applications. Different components, assets or user interests can be easily integrated and varied any time. The purpose of the tests were not to select optimal sizes for BESS or EV, but to showcase the possibilities of the proposed EMS.

However, it requires forecast for load demands as well as RES production. The developed EMS is successful in scheduling powers but it still has to be tested in real time operation. If forecast is not perfect or adjustments in BESS schedule are needed, the predefined schedule has to be modified on the run. To overcome this problem, EMS has to be tested with shorter optimization horizon, but smaller time resolution and instantaneous power dispatch. This way, by combining predictive optimized scheduling and on-the-run adjustments for power management, a full value EMS can be created. In the next chapter, the instantaneous power dispatcher algorithm for the EMS is proposed and tested.

5 | Intra-Hour power dispatch

Previous chapters has introduced the system and its components as well as proposed a DP based EMS. It has been proved to be efficient in scheduling the BESS and charging of the EV. However, managing the power flows in between scheduling points remained unsolved. This chapter will provide two strategies for instantaneous power dispatch of BESS. In order to be able to utilize DP further more, short term forecasts of RES production is required. A 24 hour analysis is conducted in order to prove the proposed dispatch strategies ability to handle uncertainties and adjust the day ahead schedule.

5.1 Component Models

To be able to analyse power flows and component behaviours in smaller time scale, more detailed models are required. These models will be used to conduct the 24 hour long simulation.

5.1.1 Inverter

One new element in the system is the inverter. It is required in order to convert DC current supplied by the PV or BESS, into AC current. The resulting AC power then either fed to the grid or utilized in the household. Furthermore, the inverter is the component which does the voltages control for PV and BESS. The selected inverters are all capable of Maximum Power Point Tracking (MPPT), meaning they automatically detect and provide the optimal voltage for the PV panels. Both the BESS and the PV panels are assumed to have a dedicated inverter to turn the DC power into AC. To be able to utilize the full potential of the PV panels the "*FRONIUS SYMO 6.0-3-M*" [108] inverter was modeled for the PV system. The inverter for the BESS is selected from the same FRONIUS inverter family [108] in accordance with the maximum power of the BESS.

To account for the self consumption of the inverter and the efficiency of the device, a proper model is required. It must be able to capture a wide variety of operating conditions, however, it has to be general enough to be applicable on most of the commercially available inverters. It was found in [109] that inverter's efficiency is mainly dependent on the input DC voltage and the output AC power. Considering the above mentioned criteria, an accurate but still simple model, namely the Sandia inverter model [110] is utilized. It is a proven method being utilized by other researchers as well [111] and can be applied by using only the datasheet parameters of the inverter. The model can determine the output AC power (and therefore efficiency) from the input DC power and voltage.

5.1.2 Battery model

The same model as mentioned in Section 3.1.4 is used. For this type of analysis only the 6.4 kWh battery is considered.

5.1.3 PV panels

As mentioned in Section 3.1.2, 16 panels of LG Neon R [91] were modeled to achieve the desired amount of installed PV power. The models which are widely used to relate G and ambient temperature (T_a) to produced DC power are based on IV curve approximation. Detailed description for the models can be found in [112], [113]. The modeled inverter has built-in MPPT capabilities, thus the DC voltage at the PV panel is assumed to be always kept at the optimum (V_{mp}) by the inverter.

5.1.4 Heat Pump and House thermal model

To account for the heat demand, a simple thermal model of a simple house is defined. The house is considered as cuboid shape with a rectangle base, walls and roof, with air inside and the layout of it can be seen in Figure 5.1.

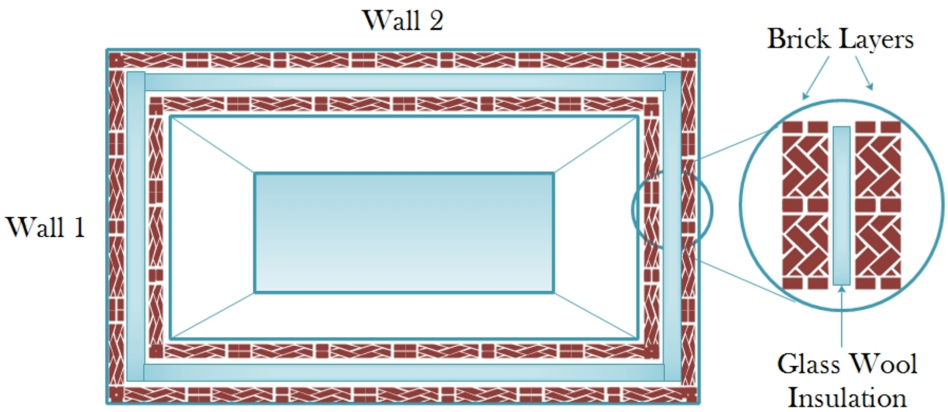

Figure 5.1: Walls

The four walls are insulated and their parameters are listed in Table C.3 and 5.2, where k is thermal conductivity and h is convective heat transfer coefficient. The walls are constructed in a way that there is insulation in the middle (glass wool) and brick is on the inside and outside, the roof is only made of insulation (for simplicity in modelling).

Table 5.1: Parameters of the house

Wall type	Dimension 1 [m]	Dimension 2 [m]	Number of layers
Wall 1	10	3	3
Wall 2	15	3	3
Roof	15	10	1

Table 5.2: Parameters of layers [114],[115]

Layer	Thickness [mm]	Material	k $\frac{W}{m \cdot K}$	h $\frac{W}{m^2 \cdot K}$
Layer 1	108	Brick	0.72	-
Layer 2	220	Insulation	0.04	-
Layer 3	108	Brick	-	
Air	-	stagnant air	-	13

The thermal model is based on basic thermal dynamics [115] and only conduction and convection heat losses are considered. Once the thermal resistances are calculated, knowing the ambient temperature and the HP ratings temperature profile in the house can be calculated. A simple ON/OFF control has been implemented with a ±0.5°C threshold around the reference temperature.

5.1.5 Wind turbine

The same power curve as in Section 3.1.1 is used during the power dispatch analysis. The model is expanded to take into account the effects of the blades inertia based on the studies in [84].

5.1.6 Charging station

During the 24 hour simulation, the charging schedule is determined by the day ahead schedule produced by the EMS. This means, that since the optimal charging time is mainly grid price dependent, the schedule for EV charging will not be adjusted during the analyses. Therefore, it can be considered as a predefined load. The charging power is always $11kW$ as discussed in Section 3.1.5. Ramp up time of the charger is neglected.

5.2 Forecasting

It is important to consider the forecast uncertainties of the renewable energy production while planning BESS or EV operation. Different forecasting techniques have been used in the literature for doing so. For example, numerical weather prediction techniques (NWP), probabilistic forecasting, ANN methods etc. [116]. The choice of the forecasting technique mainly depends on the desired time scale, forecasting horizon, and the data available for making the prediction. Table 5.3 describes the terminologies of various time scales and forecasting horizons.

The forecasting application in this thesis fall under the very short-term forecasts category, with the aim of predicting the values of the solar irradiance and wind speed for a forecasting horizon ranging from 5 minutes to 15 minutes. The most commonly utilized techniques used to assess very short-term forecast of solar irradiance and wind speed are the ones with time series analysis. The biggest advantage of them is they do not depend on actual weather forecasts [116], [117].

Table 5.3: Time Scales, Forecasting Horizons and Applications [117], [118]

Time-Scale	Forecasting horizon	Application
Very Short-Term	Few seconds to 30 minutes ahead	Real time grid operations Power System balancing Plant operations (Ex. smoothing)
Short-Term	30 minutes to 6 hours ahead	Intraday Energy Markets Load increment/ decrement decisions Economic load dispatch planning
Medium-Term	6 hours to 1 day ahead	Fuel allocation planning Day ahead energy market Generator online/offline schedule
Long-Term	1 day to 1 week (or more) ahead	Operation Management Power System Capacity planning Maintenance Planning

Time series models utilize the actual values from the past (historical data) to forecast the future values. Various methods such as Kalman filter techniques, auto-regressive models, ANN approaches have been explored in the literature for predictions considering the time series models. The simplest of these techniques are the autoregression models [116].

A basic Autoregressive Moving Average (ARMA (1,1)) model has been chosen and implemented for forecasting values minutely for the desired forecast horizon. This model uses a combination of Autoregressive (AR) and a Moving Average (MA) models to predict the next values of the data in the upcoming forecast horizon. The performance of this model is evaluated by Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Bias Error (MBE) for a range of historical data period lengths. In the next section the optimal historical period length for 15 minute forecast is found.

The evaluation of this proposed forecast strategy is performed with commonly used criteria for assessing the deviation of the predicted values from the actual ones. The most widely used criterion to perform analysis on errors is to evaluate the RMSE which is represented by Equation 5.1. RMSE calculates the standard deviation of the prediction errors (residuals). The term 'P_i' refers to the actual observations whereas, '$\hat{P}_i$' refers to the estimated values or forecasted values.

$$RMSE = \left(\frac{1}{N} \sum_{i=1}^{N} (P_i - \hat{P}_i)^2 \right)^{\frac{1}{2}} \tag{5.1}$$

MAE also known as average absolute deviation is usually accessed if there are many outliers in the sample. The considered data for wind speed and G often fluctuates abruptly depending on the weather conditions and seasons. Thus, MAE has been calculated and compared for different scenarios. MAE calculates the absolute difference between the forecasted and the actual values and can be represented as Equation 5.2.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|(P_i - \hat{P}_i)\right| \tag{5.2}$$

The algebraic difference between the forecasted and the actual values can be given by the term MBE (Equation 5.3). A positive MBE concludes that the forecasted values are overestimated, whereas, negative MBE values characterize an underestimation in the forecast.

$$MBE = \frac{1}{N}\sum_{i=1}^{N}(P_i - \hat{P}_i) \tag{5.3}$$

To show the effectiveness of the forecast, wind speed profile for a period of 24 hours (12 September 2018 - 13 September 2018) is subjected to the ARMA model in 15 minute periods. The aim is to predict the values minutely for the next 15 minutes (forecast horizon) based on the actual values recorded every minute during the historical period.

The historical period (H) refers to the number of values the forecast is based upon. The historical period, looked upon to predict the next 15 minute values, is always the most recent H number of recorded (measured) values. The effect of varying the historical period on RMSE, MAE and MBE in Appendix C. Figure 5.2 shows the 15 minute forecasted values for each iteration of the ARMA model for historical periods of (H= 100, 250 and 400 minutes) for two consecutive days, where the prediction starts at 9:00 the second day.

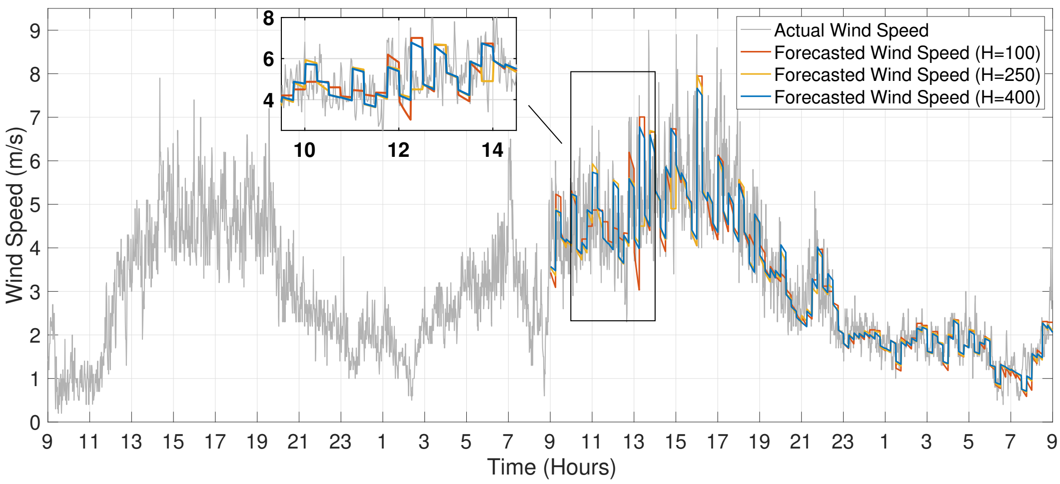

Figure 5.2: Forecasted and Actual wind speed measurements

For the purpose of deeper analysis, the deviations of these forecasted values from the actual values, i.e. the above mentioned analytical criteria (RMSE, MAE and MBE), are calculated by applying Equations 5.1, 5.3 and 5.2 to the time series of forecasted and actual wind speed measurements. Appendix C lists values of H and corresponding criteria values to observe the effect of variations of the forecasting horizon. The analysis of varying the values of historical period for forecasting horizon of 15 minutes suggests that it is best to use a historical period of 250 minutes. Conducting the same type of analysis (see Appendix C) optimal H for prediction horizons of 5, 10 and 15 minutes are listed in Table 5.4.

Table 5.4: Mean Errors

Forecast horizon	**H** [min]	**RMSE** [m/s]	**MAE** [m/s]	**MBE** [m/s]
5 minutes	225	2.29	1.87	1.41
10 minutes	100	2.27	1.85	1.39
15 minutes	250	2.28	1.86	1.39

In conclusion, H = 250 minutes when forecasting for next 15 minutes, H = 100 minutes when forecasting for next 10 minutes and H = 225 minutes when forecasting for next 5 minutes proved to be the best performing choices respectively.

5.3 Simplified forecast

A simple approach was initially formulated to forecast the wind speed and G for the next 15 minutes. This approach assumed that the values stay the same for next 15 minutes.

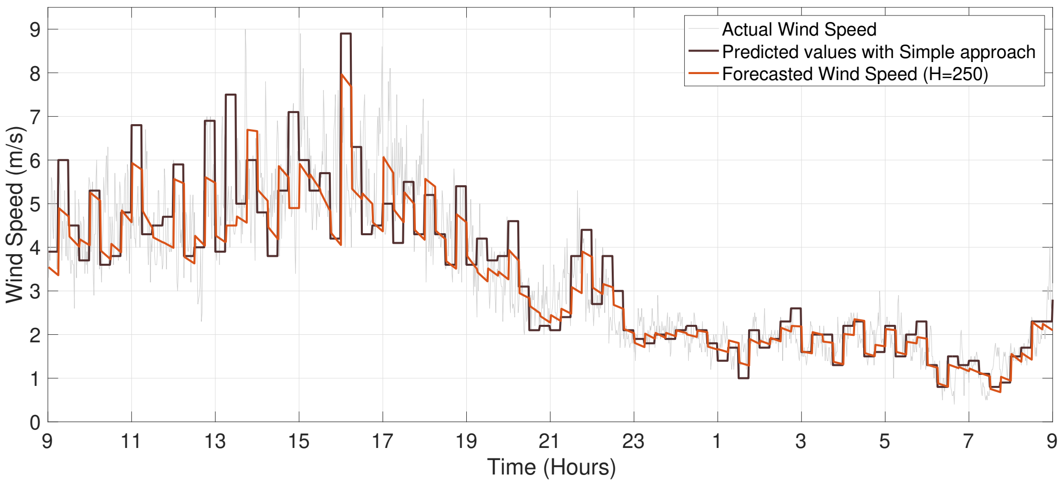

Figure 5.3: Comparison of forecast with simple approach and ARMA(1,1)

Table 5.5 lists the criteria assessment against the ARMA forecasted values for H = 250 minutes (the best scenario). Figure 5.3 shows the wind speed predicted with this simple approach against the wind speed forecasted with the ARMA(1,1) model discussed in the section above as well as the actual measured wind speed. When tuned correctly with respect to the constants for ARMA model and required historical period (H) and forecasting horizon, the forecasted values with the ARMA model result in better performance suggested by the analytical criteria.

Table 5.5: Mean Errors against ARMA forecasted model (H= 250 min)

	RMSE [m/s]	**MAE** [m/s]	**MBE** [m/s]
Simple forecast	2.37	1.95	1.50
ARMA forecast	2.28	1.86	1.39
Improvement (%)	4	4.9	8

As the ARMA(1,1) model has been proven to be an effective tool for very short term forecasting, it will be used in the upcoming analysis.

5.4 Dispatch strategies

Two approaches have been implemented for the rescheduling of BESS power references. Both of them utilize the short-term forecast for wind speed and irradiance and applies DP to schedule the battery for the next short period. Firstly, a 24 hour ahead schedule is made by the EMS at 9 am. It utilizes weather forecast data as well as approximated load profile, prices from Nordpool [41] and a temperature reference (for the HP) for the next 24 hour. The 9 am to 9 am interval has been selected to ensure that the arrival and departure time of the EV is included in the optimization horizon of the first level, since these parameters are needed for the EMS to optimally schedule its charging time.

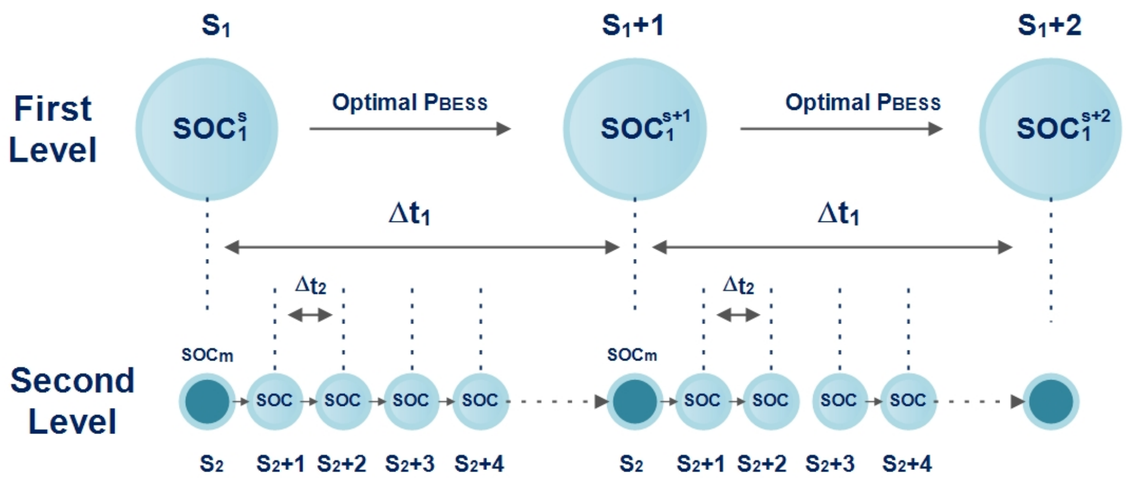

Figure 5.4: Two level DP

The time resolution (Δt_1) of this day-ahead schedule is dependent on the user and will be a subject of study during the analysis. The user can also select how often (t_2) should the EMS adjust its schedule and give power references for the battery. However, the time between stages in the second level (Δt_2) is set to $\Delta t_2 = 1$ minute, i.e. if the optimization horizon (of the second level) is set to 10 minutes, the second level has to provide 10 reference points for the BESS for the next 10 minutes. To further understand the concept of a two level EMS scheduling, Figure 5.4 shows the most important aspects of the structure.

The first level is the day-ahead schedule already showcased in Section 4.2.1. The dispatcher is the second level, which is responsible to give power references to the battery in between the original stages and incorporating the newly acquired measurements and short term forecasts. In the next sections, two proposed approaches will be explained.

5.4.1 Following SOC reference

The first approach is taking the day-ahead schedule as the reference for the battery's SOC. The idea is, that the rescheduling is conducted between two adjacent stages in the day-ahead schedule. Between stages S and $S+1$, a second DP based scheduling can be conducted to optimize the transition with a finer time and hence SOC resolution. As explained in Chapter 4, DP needs the state in the last stage defined in order to give the optimal policy for that particular end state.

In this approach these end states would be provided by the day-ahead schedule. If the reschedule is done more frequently then the time between two stages in the day-ahead schedule ($t_2 < \Delta t_1$), then the end states can be linearly interpolated between the original schedule's optimal SOC states. The SOC resolution of this second level DP (δSOC_2) can be selected by the user and again will be a subject of study during the analysis. Inputs for the second level are:

- Short term forecast values of wind speed and irradiance (see Section 5.2)
- The current SOC level of the battery (measurement)
- Grid price and FIT in the next period
- Current general electrical load of the house (measurement)
- Current HP consumption (measurement)
- EV charging power (available from day-ahead schedule)
- SOC_{BESS} values from the day-ahead schedule

This way the battery follows the same SOC path as it was predefined in the day-ahead schedule. The advantage is that the battery now can react to real-time values and can adjust its power profile to better fit the actual situation. Assuming that the day-ahead forecast achieved to capture the trends in RES production and load profile for the next 24 hour, fine tuning the SOC path during the day can lead to better performance. The disadvantage of this approach is that it is still rigid in terms of SOC path and can lead to lower performance if day-ahead forecast and real values are significantly different during the day.

5.4.2 Following grid power reference

The second approach was inspired by [119] and also utilizes DP for the second level rescheduling. The main idea is that the second level is minimizing the deviance between the actual grid power and the optimum one (calculated by the first day-ahead level), instead of the cost. This way the battery can react more actively to the changes in load and RES production as it has no predefined SOC path to follow. Therefore, utilizing this approach the SOC values from the first level can no longer be used as a reference. Here, the scheduled grid power is used as the reference. The second level DP is still conducted between the original stages, the initial SOC state is the one which is measured at the beginning of the schedule. Then, using the battery's maximum power constrains the reachable SOC_{end} states are bounded by Equation 5.4:

$$SOC_{end}^{max/min} = SOC_{BESS}^{current} \pm P_{BESS}^{max} \cdot t_2 \tag{5.4}$$

The EMS uses DP to calculate the optimum schedules (which minimizes grid power deviance) for every SOC_{BESS}^{end} state which falls into the defined range above. Finally, the EMS selects the final SOC state which has the optimal policy with the minimal accumulated difference between the optimal grid power and the calculated one in the second level. Inputs for the second level are:

- Short term forecast values of wind speed and irradiance (see Section 5.2)
- The current SOC level of the battery (measurement)
- Grid price and FIT in the next period
- Current general electrical load of the house (measurement)
- Current HP consumption (measurement)
- EV charging power (available from day-ahead schedule)
- P_{grid} power references from the day-ahead schedule

With this approach the battery is not bounded by the predefined SOC path and can act more freely. Since the estimated grid cost is calculated from the estimated grid power, this approach could achieve daily cost closer to the estimated one than the first approach. Moreover, this approach provides a more reliable grid profile as it can serve as a plan for the local Distribution System Operator (DSO).

The disadvantage of this method is that the end of the day SOC is not guaranteed. The user can select the desired end of the day SOC for the first level and the day-ahead schedule will be done according to that. Nonetheless, the actual end of the day SOC will depend on how much the battery had to deviate from the schedule due to the uncertainties and errors in the forecast.

5.5 Verification of dispatcher

In the next sections the two approaches will be tested with varying parameters to find the optimal or most favourable combination.

5.5.1 Input data

To analyse the impact of different parameters and methods, the same input profiles will be used. The temperature reference for HP is shown in Figure 5.5.

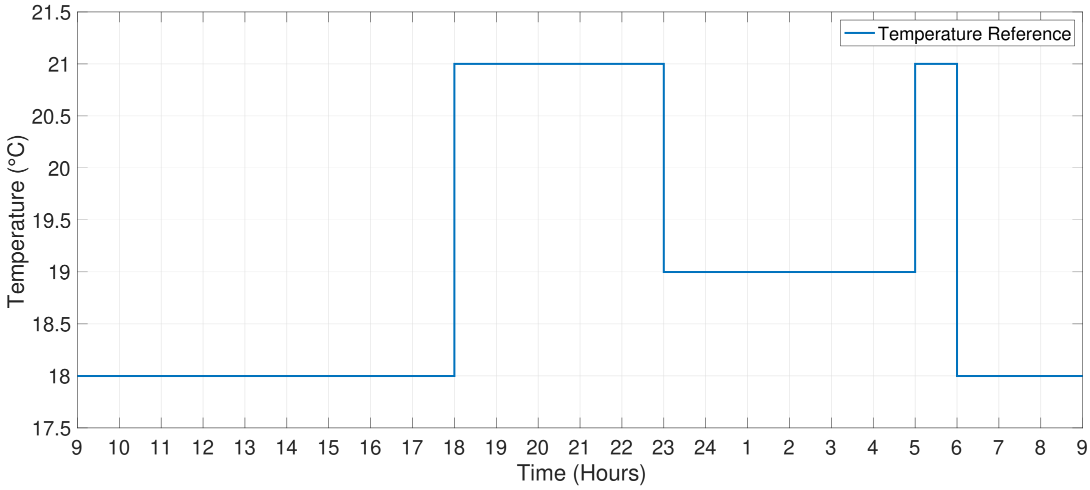

Figure 5.5: Temperature reference during the 24 hour period

It follows the pattern of the EV departure and arrival times. The irradiance, wind speed and external temperature data is minutely sampled and has been recorded between 09:00 am 11.09.2018 and 09:00 am 13.09.2018 [40]. The load data is 15 minutely sampled, recorded on the same day and provided by Aalborg University. To further examine the system's effectiveness, the load profile has been subjected to a $\pm 10\%$ variation to emulate uncertainties.

The load profile can be seen in Figure D.5. The spotprice data is fetched from Nordpool [41] for the same period as mentioned above and is hourly sampled. All of these profiles and the rest of the input data can be seen in Appendix D. The reason to have 2 days of data for the irradiance and wind speed is to have historical data right away at the start of the analysis. During the day-ahead schedule the EV is expected to arrive at 19:00 and leaves the next day at 07:00.

5.5.2 Base case

Similarly to Section 3.2, first a base case has been set up without the EMS and BESS. With the above specified inputs for the 24 hour period is studied. The calculated P_{grid} for the studied period, can be seen in Figure 5.6.

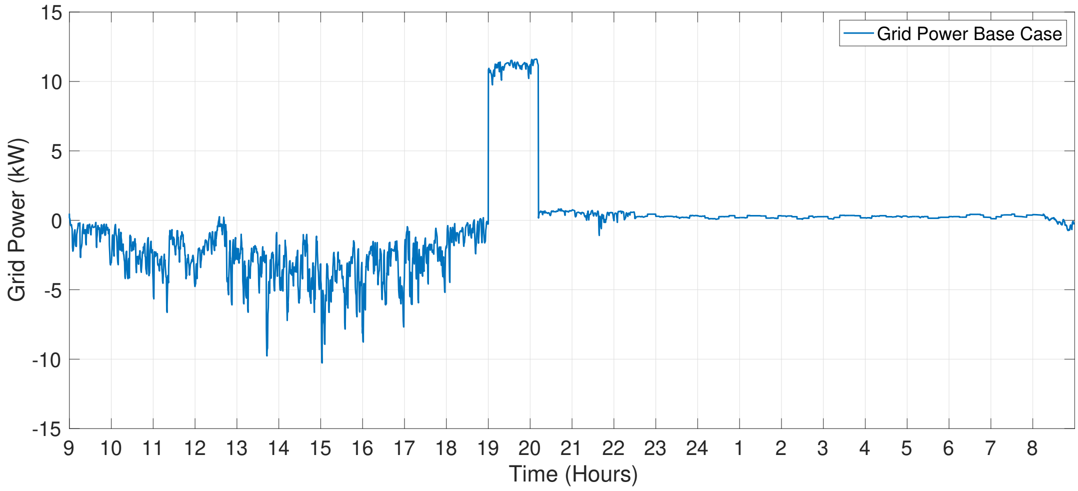

Figure 5.6: Grid power profile without EMS or BESS

The resultant grid price at the end of the period is 27,95 DKK. In the following section, this value will serve as the base comparison. The savings will be calculated with regards to this cost.

5.5.3 Study cases

There are three main parameters which can be varied in DP to alter the results. The SOC resolution (δSOC) which is directly connected to the number of states, the time resolution (Δt) which gives the number of stages and the optimization horizon (t) which defines the length of the schedule. For a two level system it results in 6 main parameters. In the first level t_1 is selected to be 24 hours and in the second level Δt_2 has been kept constant at 1 minute. Hence, during the analysis the other 4 parameters (Δt_1, δSOC_1, δSOC_2, t_2) are varied.

To keep the number of cases reasonable and to prevent unfeasible combinations the connection between δSOC and Δt has to be pointed out. Using the battery power constraint (Equation 4.6) and Δt, a maximum SOC change between adjacent stages can be defined by Equation 5.5:

$$P_{Bat}^{max} \cdot \Delta t = \delta SOC^{max} \tag{5.5}$$

If ΔSOC^{max} is smaller than δSOC, then the only possible choice for the EMS is to set the power reference to 0 preventing the battery from functioning. To avoid this problem δSOC and Δt are always selected in a manner that the EMS has enough options for the battery power reference. Table 5.6 summarizes the possible values for δSOC and Δt for both levels.

Table 5.6: Possible δSOC and Δt values

	δSOC	Scheduling rate [min]	Reference
First level	0.1, 0.01	15, 30, 60	-
Second level	0.005, 0.001	5, 10, 15	SOC, P_{grid}

Combining every parameter described in Table 5.6 yields in 36 cases per approach with a total of 72 cases. The rest of the input parameters (like SOC_{init}, SOC_{end}, etc... and constrains) can be found in Table D.1.

5.6 Results for dispatcher verification

The results of all cases can be found in Appendix D. Here some of the cases will be presented to highlight the effects of different parameters.

5.6.1 Approach one - SOC reference

The first case presented has been conducted with the parameters in Table 5.7. Figure 5.7 shows the day ahead (first level) schedule. The EV has been scheduled to 4 am when the grid prices are low, the battery charges during the afternoon where wind production is high.

Table 5.7: δSOC and Δt values for case 1

δSOC_1	Δt_1 [min]	δSOC_2	Δt_2 [min]
0.01	15	0.001	5

The BESS covers most of the load demand during the evening and all through the night, just to arrive back at the predefined 50 % charge level in the next morning. The middle two plots represent the BESS power and SOC profiles.

The first one shows the prescheduled power profile as well as the actual one which was altered by the dispatcher. The second one depicts the planned (day-ahead scheduled) SOC profile and the one which actually took place. The very first conclusion is that the dispatcher adheres to the predefined SOC profile and was able to follow it during the examined period.

The difference between the two SOC profiles can be seen in-between two adjacent original 15 minute SOC reference points. Since the dispatcher adjusted the reference points every 5 minutes, the power profile (and hence the SOC profile) gets a higher resolution.

It can be also seen on the BESS power profile, the actual BESS power is more volatile as it reacts to the measured and short term forecasted values. Nevertheless, the power profile still roughly follows the predefined curve as the first level SOC profile strictly bounds to it. The last graph shows the scheduled grid power and the measured one. The measured grid power changes more rapidly as it follows the changes of all RES production and assets on the demand side.

As the 24 ahead forecast is not perfect and has a lower resolution (maximum 15 minute), the actual grid power differs from the anticipated one. This can cause issues when the RES production is overestimated in the day ahead forecast. For instance, between 16 and 17 pm the grid power was expected to be negative but instead, due to the lack of wind power, it was highly positive (meaning buying electricity).

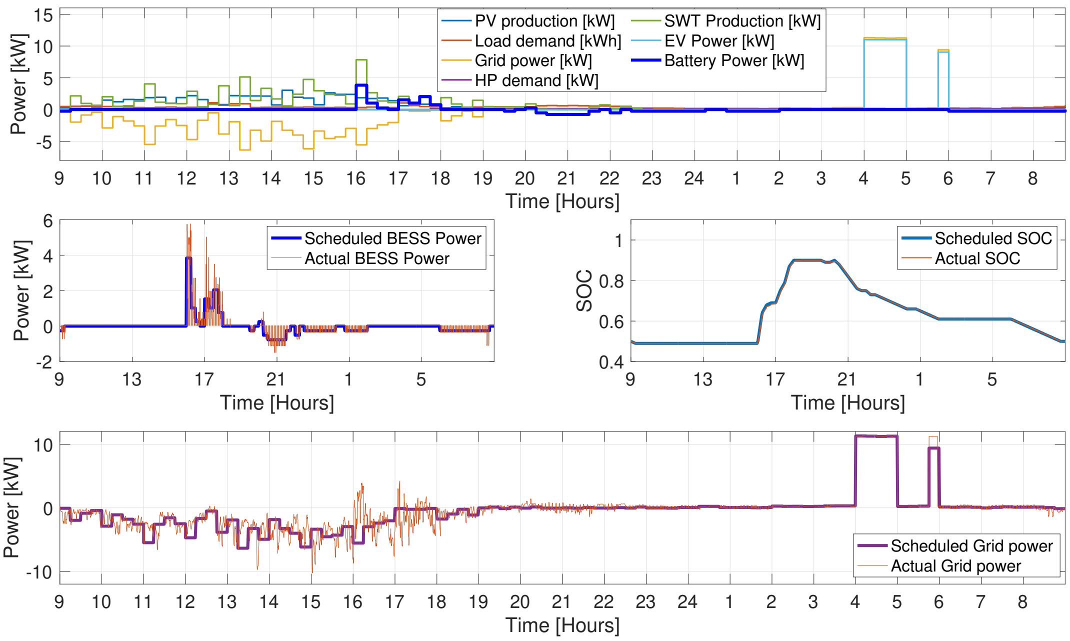

Figure 5.7: Case 1 power and SOC profiles

In the next case, only Δt_1 has been changed, to 30 min. The parameters can be seen in Table 5.8. As now the day ahead resolution is lower, the BESS schedule has less capability to capture the events of the next day. However, this "flaw" is proven to be an advantage when it comes to the dispatcher.

Table 5.8: δSOC and Δt values for case 2

δSOC_1	Δt_1 [min]	δSOC_2	t_2 [min]
0.01	30	0.001	5

Given the fact that there is a bigger time gap between original set points, the dispatcher has a higher wriggle room to adjust the power profile. This results in a slightly better end of the day overall cost (see Table 5.11). The power profiles of the day ahead schedule can be seen in Figure 5.8.

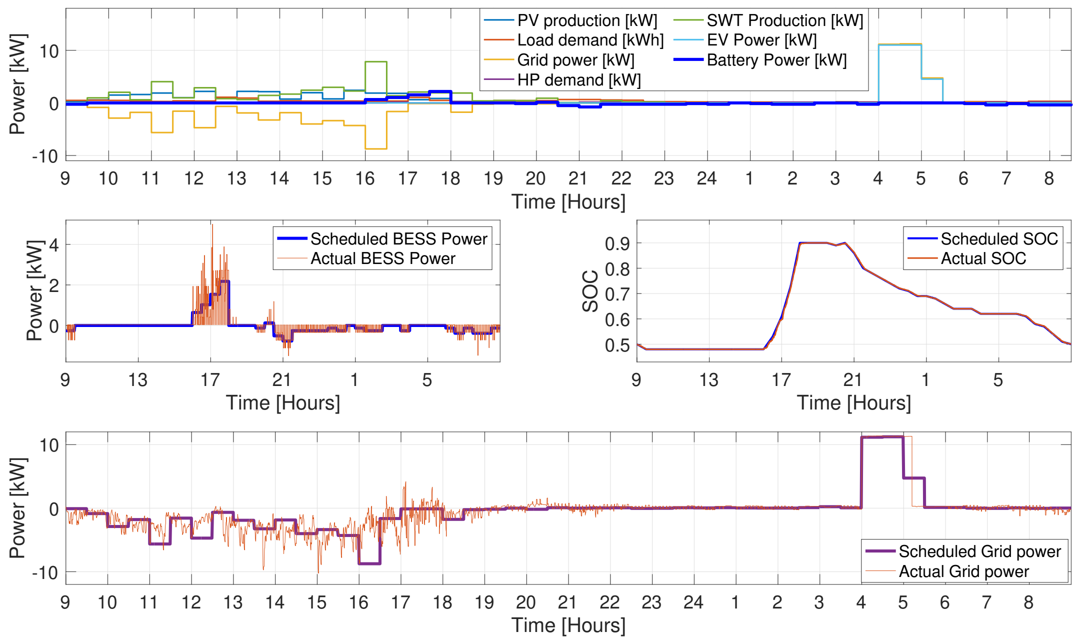

Figure 5.8: Case 2 power and SOC profiles

To see the full effect of varying Δt_1, it has been set to 60 min, see all the parameters in Table 5.9. This means that the first level only has 24 stages. While weather and load forecast is easier to gather with hourly resolution, it also can be too vague and eventually too misleading (if wrong) for the BESS SOC reference profile. Figure 5.9 shows the power profiles for this case.

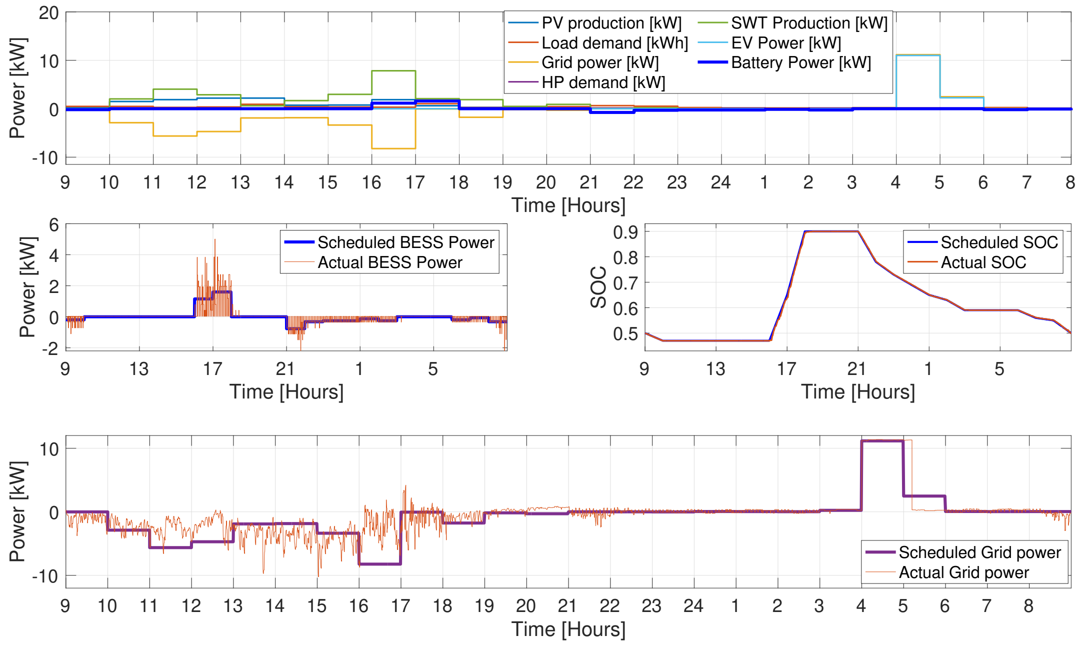

Figure 5.9: Case 3 power and SOC profiles

Table 5.9: δSOC and Δt values for case 3

δSOC_1	Δt_1 [min]	δSOC_2	Δt_2 [min]
0.01	60	0.001	5

The expected and actual grid powers are deferring even more as the uncertainties grow with Δt_1. Finally, the decreased time resolution in the first level, does yield in increased overall costs. However, it can be stated that every case has a significantly better performance than the base case without EMS or BESS.

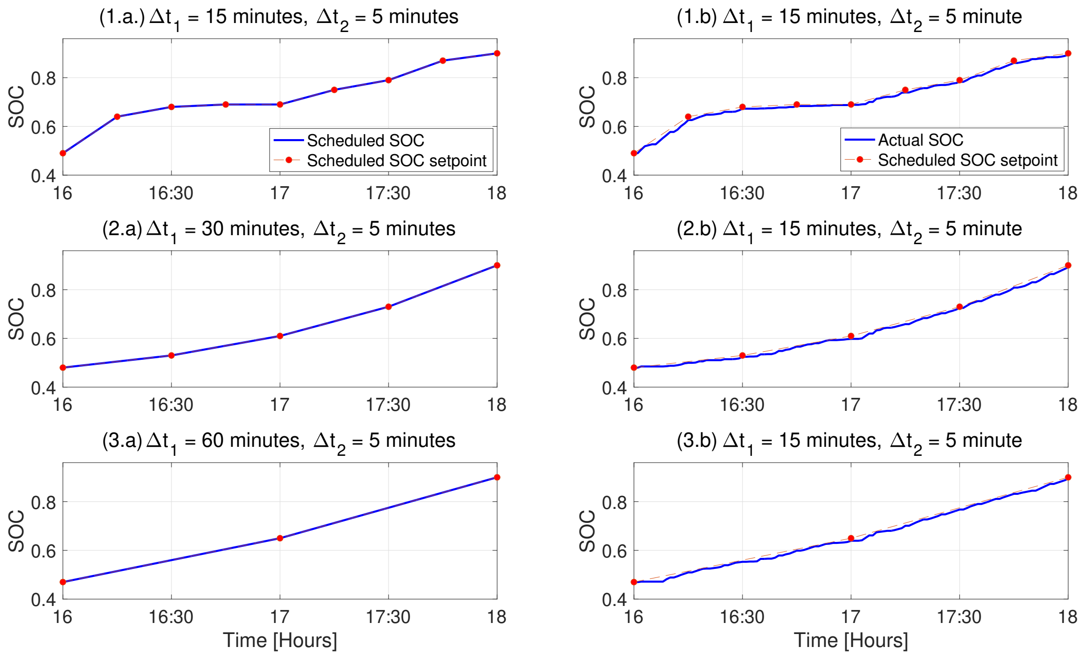

Figure 5.10: Actual and day-ahead SOC profiles

To better understand the method defined in Section 5.4.1, Figure 5.10 depicts the day ahead and actual SOC profiles of the battery for every previously mentioned case between the hours of 16 and 18 pm.

First of all, the SOC profiles follow the same reference points creating an inevitable path for the battery. Second of all, on the right hand side, the actual profiles show a completely different route between two adjacent reference points. This is the results of the dispatcher reacting to real time events while following the predefined schedule. Without showing every power profile, Figure 5.11 helps describing the effect of δSOC_2. The previous case is compared to one where the only difference is the increased resolution of δSOC_2. In that case the parameters in Table 5.10 have been used.

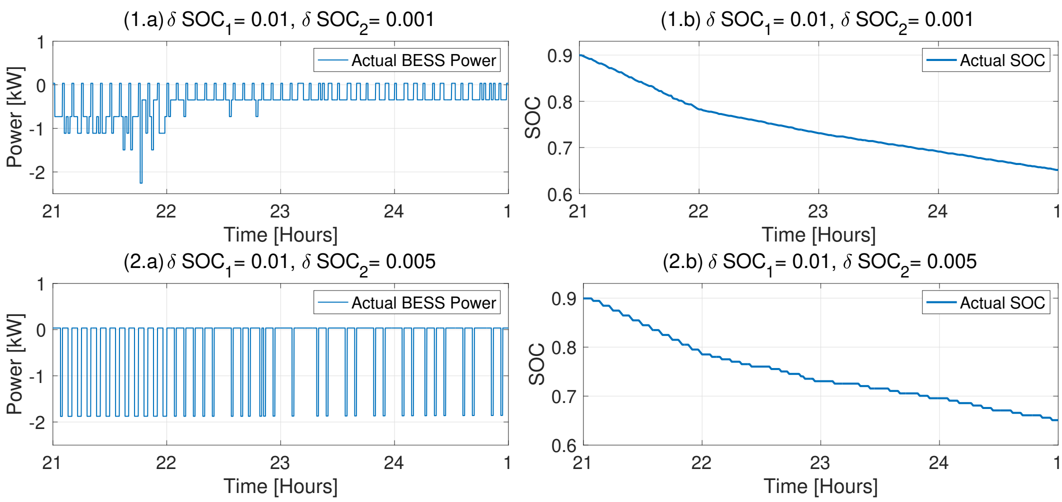

Figure 5.11: P_{BESS} and SOC for $\delta SOC_2 = 0.001$ vs $\delta SOC_2 = 0.005$

Table 5.10: δSOC and Δt values for case 4

δSOC_1	Δt_1 [min]	δSOC_2	t_2 [min]
0.01	60	0.005	5

While the decreased δSOC_2 resolution has its advantages in terms of computational performance, it is highly outweighted by the disadvantages it brings for flexibility of the BESS. Case 4 operates with much less feasible states in the second level, meaning the battery can only be scheduled to one sufficient power output. While the $\delta SOC_2 = 0.001$ case provides a much wider spectrum of power set points for the battery. The results of higher δSOC_2 resolution are decreased battery and overall costs. The summary of costs of these cases can be seen in Table 5.11.

Table 5.11: Summary of costs of presented cases

	Grid cost [DKK/day]	BESS cost [DKK/day]	Overall cost [DKK/day]	Saving [%]
Case 1	15.20	1.71	16.91	39.50
Case 2	15.12	1.75	16.87	**39.63**
Case 3	15.30	1.77	17.07	38.91
Case 4	17.27	2.10	19.37	30.69

5.6.2 Approach two - P_{grid} reference

The second approach utilizes the day-ahead schedule's grid power as a reference. Therefore, it dispatches the battery with the goal to minimize the actual grid power's deviance from the reference. Here the first case has the same parameters (listed in Table 5.7) as the first case in Section 5.6.1. The difference is the mentioned dispatch strategy. The first graph in Figure 5.12 shows the day-ahead scheduled power profiles. It is exactly the same as the on Figure 5.7 as the data and parameters used for the first level are identical for this two cases.

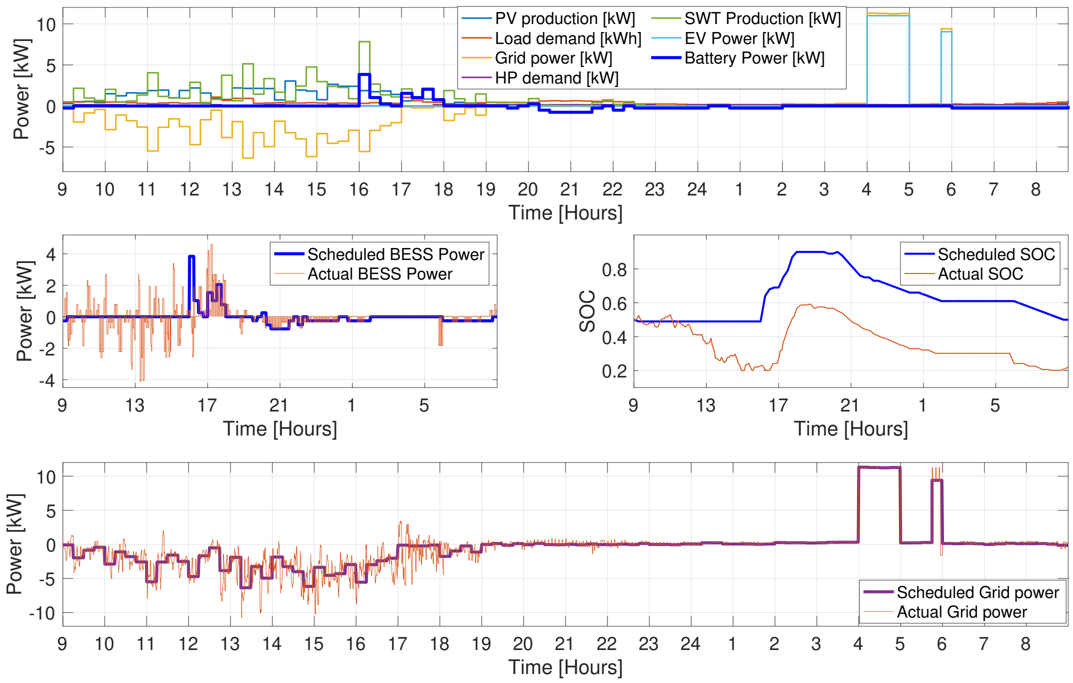

Figure 5.12: Case 1 power and SOC profiles

Likewise, the scheduled BESS power and SOC profiles are also identical to the ones in Figure 5.7. However, the difference between the two dispatch strategies become clear when the actual battery and grid power profiles of the two cases are compared. Here the battery power profile heavily differs from the scheduled one, hence the SOC profile also deviates. In the first period of the day, the volatility of RES forces the battery to act, to be able to follow the grid power reference.

At night, when both consumption and production is at minimum, the scheduled power profiles resemble more the actual ones, therefore the SOC profile follows a similar path (but with on offset from before). With this approach the household is able to follow much better the day-ahead grid power profile, meaning it can provide a reliable plan for the local DSO. To illustrate how better this method is able to follow the grid reference, Table 5.12 lists the RMSE values for the grid profiles for case 1 from the previous section and this case, where the only difference is the utilized dispatch method.

Table 5.12: RMSE values for the two methods

	Approach with SOC reference	Approach with P_{grid} reference
RMSE [kW]:	1.3952	1.16

The P_{grid} reference approach has reduced the deviance with more than 16 %. Nevertheless, at the end of the day the overall cost for this method is somewhat higher compared to the previous approach. This is due to the lack of energy in the battery during the evening, as it was depleted along the day to cover the missing RES production.

To also examine the effect of the rescheduling rate, the next two cases will hold every other parameter constant, but varies t_2. The exact parameters can be seen in Table 5.13.

Table 5.13: δSOC and Δt values for case 2 and 3

	δSOC_1	Δt_1 [min]	δSOC_2	t_2 [min]
Case 2	0.01	15	0.001	10
Case 3	0.01	15	0.001	15

The day-ahead schedule stays the same, but the battery profiles show a different picture. The 10 minute rate offers less flexibility and rarer actual measurements are involved in the process which can lead to bigger errors in the grid power profile as it can be seen in Figure 5.13.

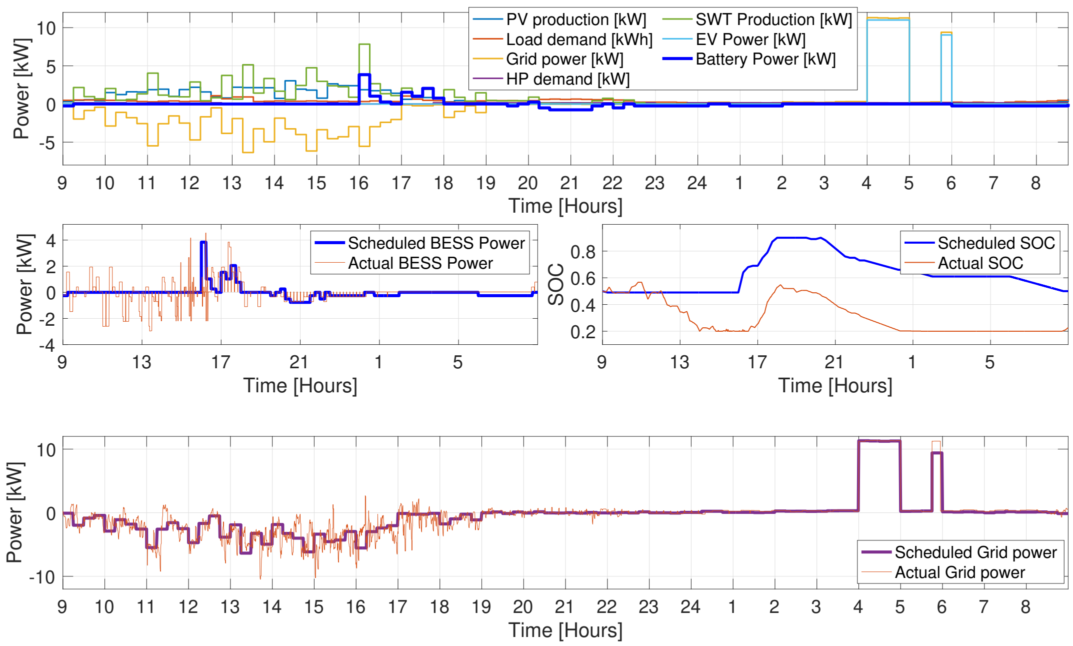

Figure 5.13: Case 2 power and SOC profiles

The most significant difference between the previous and this case, is that the battery is not able to charge as much in the late afternoon. Thus, it did not have enough reserve for the evening and from midnight it reached its allowable minimum. This case yielded in a slightly higher grid cost, but due to the reduced battery activity it was more gentle with the BESS, resulting in less degradation cost.

Overall these two effect balanced out each other.

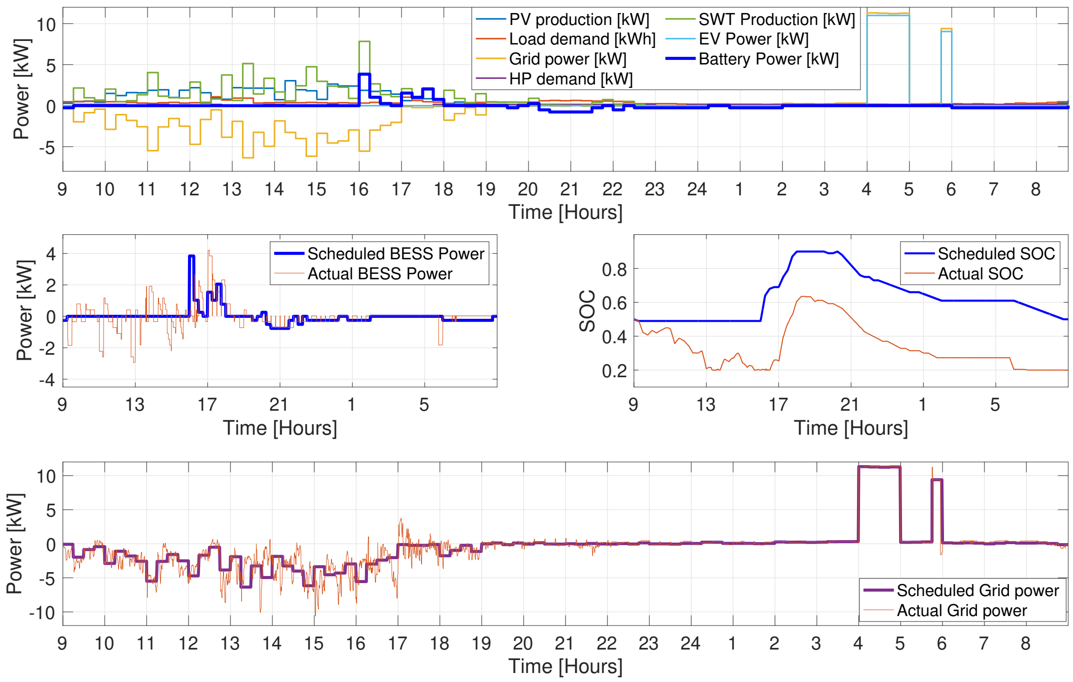

Figure 5.14: Case 3 power and SOC profiles

Figure 5.14 depicts the case with Δt_2 of 15 minutes. This case has the same rescheduling rate as the first level's time resolution. The battery acts more reserved in this case and it is able to save some energy for the evening.

The saved energy plays an important role as it allows the battery to cover most of the surplus power needed to charge the EV (for the second time) during the early morning hours. It is a good example to showcase the goal of this approach of following the grid reference. The summary of costs of these cases can be seen in Table 5.14.

Table 5.14: Summary of costs of presented cases

	Grid cost [DKK/day]	BESS cost [DKK/day]	Overall cost [DKK/day]	Saving [%]
Case 1	14.33	3.54	17.88	36.04
Case 2	14.91	2.99	17.90	35.97
Case 3	13.79	2.88	16.67	**40.35**

A zoomed time window of the actual and reference grid power profiles of these cases can be seen in Figure 5.15.

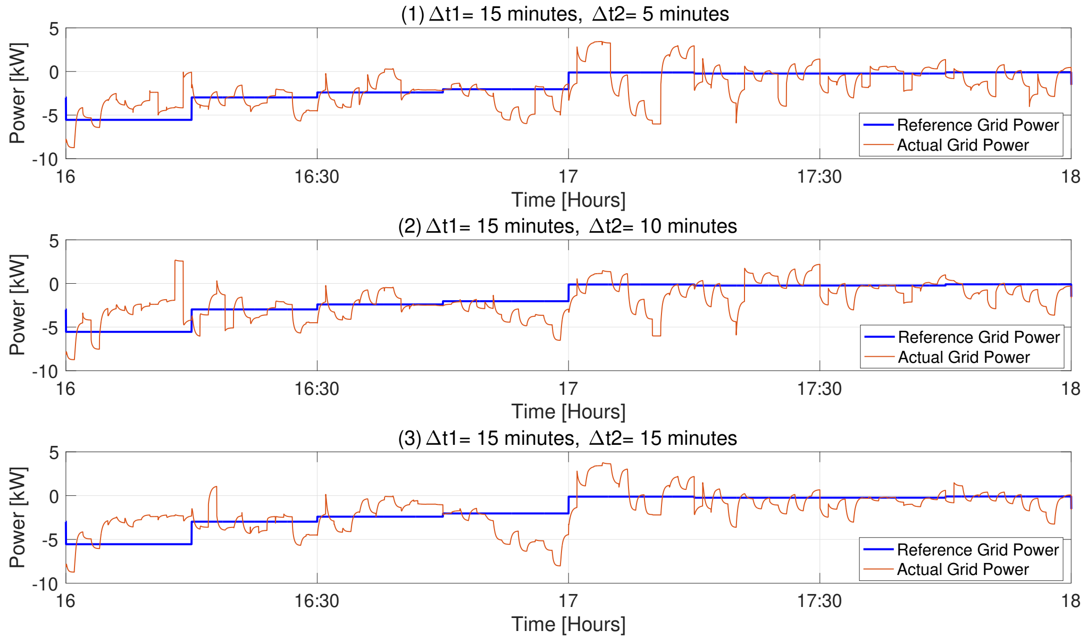

Figure 5.15: Actual and reference grid power profiles

As already mentioned the reference is the same. The effect of t_2 is clear. With more often rescheduling the grid power is following the reference with smaller error, however, at the expense of a more intensively used battery. Finally, to emphasize the effect of δSOC_2 (which was already touched on in Section 5.6.1, in Figure 5.11), Figure 5.16 depicts the BESS SOC and power profiles for a 4 hour long period for two cases. Case 3 and a case with same parameters but $\delta SOC_2 = 0.005$.

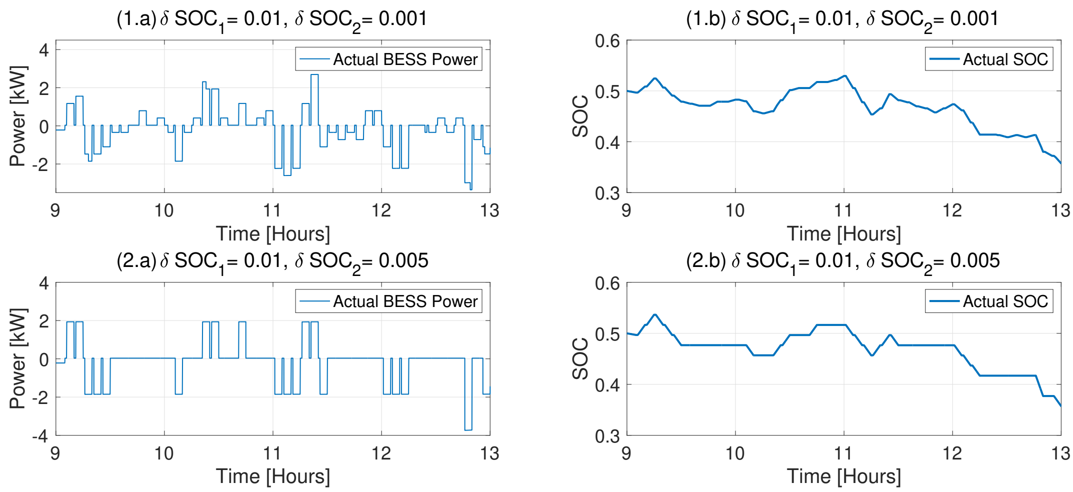

Figure 5.16: P_{BESS} and SOC for $\delta SOC_2 = 0.001$ vs $\delta SOC_2 = 0.005$

The greater flexibility lets the battery act more precisely to real time events. Even though the rough outline of the profiles resemble to each other, the small differences on the long run yield in a significantly smaller end of the day costs. While lesser δSOC_2 resolution spares the battery, it restricts it so much, that the grid prices increase substantially.

5.7 Summary

This chapter focuses on the actual dispatch strategy of the developed EMS. A two level DP based EMS has been proposed with two possible approaches for the dispatch strategy. The first level schedules the EV charging and BESS power profile for the next 24 hour. The second level adjusts the BESS power profile by reacting to actual measurements and giving more frequent reference points to the battery. Statistical methods have been utilized for short term forecast as it was proven to be more effective than keeping measured values constant. After examining the effect of the two approaches the following major conclusions can be drawn:

- Both dispatch strategies have been proven to be greatly effective in terms of implementing the day-ahead schedule and then adjusting it to react real time events.
- The SOC reference approach on average is able to provide savings of 35.74% compared to the base case. The best case yielded in a cost reduction of 42.87%.
- The P_{grid} reference approach on average is able to provide savings of 25.72% compared to the base case. The best case yielded in a cost reduction of 40.35%.
- The P_{grid} reference approach generally utilizes the battery more and results in higher degradation costs (see Table D.5).
- If the day-ahead schedule is able to capture the trends correctly, the SOC reference approach can provide greater cost reduction on average. However, this margin shrinks when it comes to the best performing parameter combinations (42.87% vs 40.35%).
- The SOC reference approach seems to benefits the prosumer better, while the one with P_{grid} reference can also provide advantages to the DSO. It utilizes the battery to follow the household's grid power reference, which increases planability.

Varying the parameters have had great effect also:

- Increasing the rescheduling rate (t_2) greatly rises the degradation cost. On one hand, it has an ambiguous effect on the grid costs if the SOC reference approach is implemented. On the other hand, it generally yields in lower cost if the P_{grid} reference approach is utilized.
- Results indicate (Table D.4 and D.7) that generally, if better forecast is available, decreasing Δt_1 (increasing the number of stages in the first level) has an advantageous effect on the savings.

- Increasing the δSOC_1 resolution is clearly beneficial if the SOC reference approach is utilized, but has contradictory results when the P_{grid} reference approach is implemented. Nevertheless, the best performing case utilizes $\delta SOC_1 = 0.01$ for both cases.
- δSOC_2 has the clearest influence on the system's performance. Finer resolution provides greater flexibility for the battery and consistently yields in bigger cost reductions.

The study cases has been shown that the proposed dispatcher methods are successful in rescheduling and achieving their goals. From these cases the best performing case's parameters are listed in Table 5.15 for both approaches.

Table 5.15: Best case parameters

	δSOC_1	Δt_1	δSOC_2	t_2
P_{grid} reference	0.01	15 min	0.001	15 min
SOC reference	0.01	15 min	0.001	10

The ability to adjust the first level's schedule is key to achieve optimal power flows. The dispatcher is utilizing the first level's rough optimum and polishes it to ensure efficient operation even during unexpected events or uncertain forecast. In the next chapter a laboratory validation will conducted, to prove the feasibility of the proposed EMS.

6 Laboratory Validation

It is important to validate the DP optimized EMS developed in the last chapters. The Smart Energy Systems Laboratory at Aalborg University is equipped with a setup consisting of PV and Energy Storage (PVES setup) and flexible loads. This chapter describes the laboratory setup and results obtained during validation of the developed DP based EMS.

6.1 System Components

The subpart of the system implemented in Chapter 3, consisting of PV, BESS, loads and EMS is considered for implementation in the laboratory due to the availability of these components. Figure 6.1 shows the components of the laboratory setup.

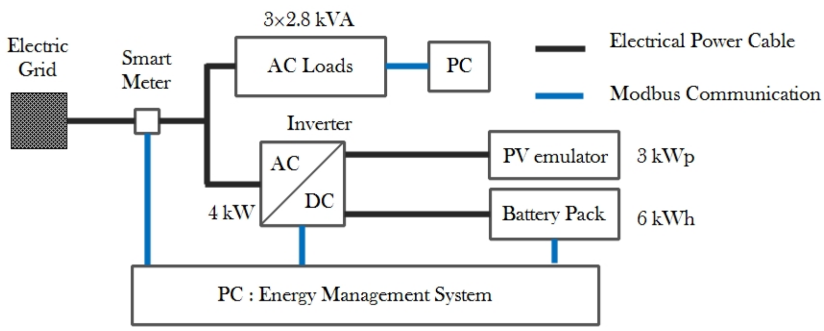

Figure 6.1: Laboratory setup components

The commercial names of the components available in the laboratory are listed in Table 6.1. A brief description of these components is provided below.

Table 6.1: Summary of equipment in Laboratory Setup [120]

Laboratory Setup	Equipment	Name
PVES Setup	Solar Converter	Fronius Symo Hybrid 3.0-3-S [121]
	PV Emulator	ITECH IT6527C DC power supply [122]
	Li-ion ES	BYD H6.4 battery pack [98]
Load Setup	Single phase loads	3x H&H ZSAC 2826 electronic loads [123]

6.1.1 PV emulator

The Smart Energy Systems lab is equipped with a 3 kW PV emulator that is connected to the grid using a commercial solar inverter (see section 6.1.2). The PV emulator is proficient enough to emulate different PV arrays involving variety of irradiance profiles and cloud shading effects. It is possible to input different irradiation profiles, temperature profiles and characteristics for the PV panels as required.

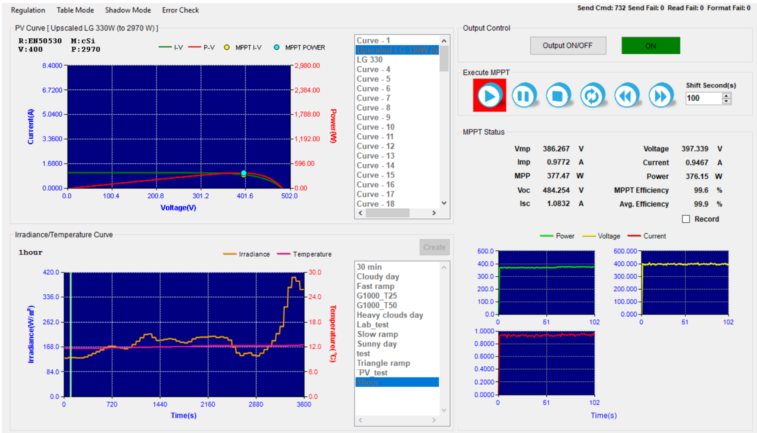

Figure 6.2: PV emulator Interface

The PVES setup along with the inverter is ideal for performing studies relating to energy management. It facilitates the charging of the Li-ion ES (Lithium Ion Energy Storage) from the PV emulator by keeping the SOC of the Li-ion ES within permissible range and restricting the power consumed by the ES or grid [124].

Figure 6.2 depicts a screenshot of the live graphical interface of the PV emulator during a test run showing the selection of IV-curve, Irradiation data, External Temperature data and MPPT status along with the emulated power, voltage and current. For all the test cases 9 of LG's 330 Wp solar panel [125] has been emulated adding up to a total of 2.97 kWp solar plant.

6.1.2 Grid Inverter

A grid connected solar converter connects the PV emulator, the Li-ion ES and the loads. A 4 kW 'Fronius Symo Hybrid 3.0-3-S' is available in the lab for this purpose. The live graphical interface of the inverter component is shown in Figure 6.3 (a). Figure 6.3 (b) shows the inverter component.

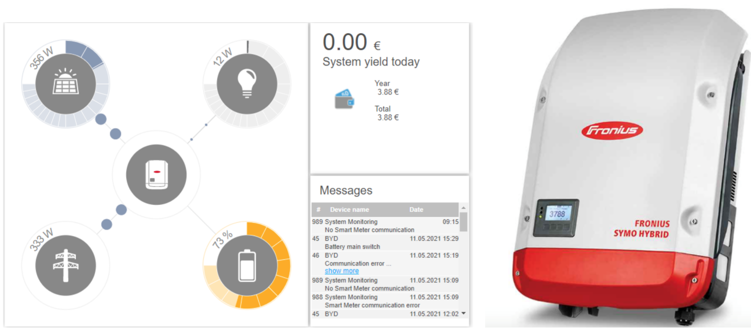

Figure 6.3: (a) Inverter Interface (b) Fronius (Symo Hybrid 3.0-3-S) Inverter[121]

The graphical interface shown in Figure 6.3 (a) shows the directions and values of the power flows between the different components (battery, grid, loads and PV emulator)

6.1.3 Battery Pack

The laboratory is equipped with BYD battery pack of 6.4 kWh capacity. It is suitable for testing energy management systems designed for household levels. The battery is compatible with the Fronius inverter. Figure 6.4 shows the complete panel for PV emulator (ITECH DC supply), Fronius Inverter and the BYD battery bank available at the laboratory.

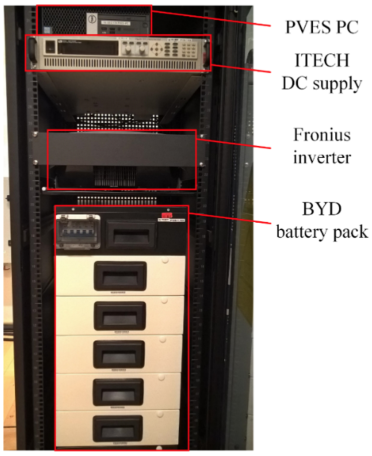

Figure 6.4: PV emulator, Inverter and BYD battery

6.1.4 Flexible Loads

Three (1 per phase, programmable) AC loads of 2.8 kW are available at the laboratory for emulating the usual electrical consumption for an apartment, farm or house. Predefined profiles based on real measurements or probabilistic models can be used depending on the season, weekdays, weekends. The time of use, probability of use and also the phase to which the load is connected can be chosen. Figure 6.5 shows the loads and the graphical interface.

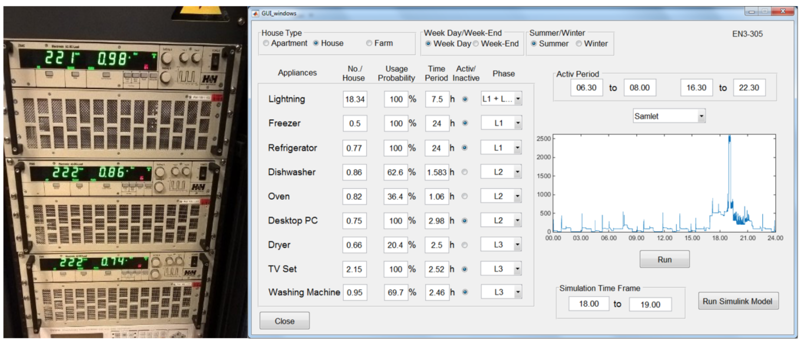

Figure 6.5: (a) Flexible Loads (b) Load Interface

6.1.5 Communication

The PV emulator is controlled via an interface (shown in Figure 6.2) and communicates with the user PC through Ethernet connection. The BESS is controlled through MATLAB/Simulink and is connected to the inverter via modbus. The loads are controlled via a MATLAB GUI and Simulink.

6.2 Base Case

In order to serve as a comparison to the EMS, a test with only the PV and the loads is conducted. The load reference from Figure 6.6 as well as the G and T_a references are fed into the H&H loads and the PV emulator respectively. The load reference was produced by the interface mentioned in 6.1.4 with 1 second sampling.

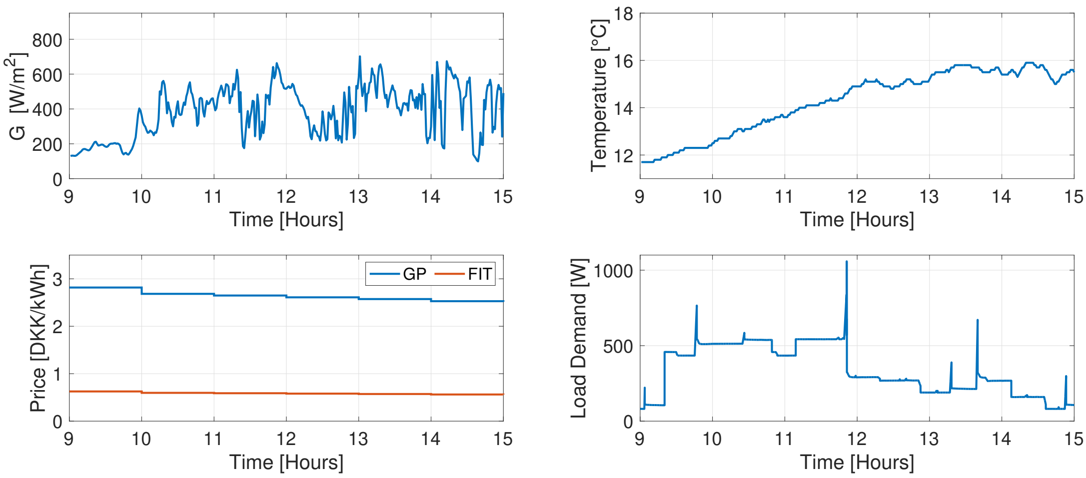

Figure 6.6: Inputs for the laboratory runs

The temperature and G profiles has been recorded on 12.09.2018 between the hours of 9am and 15pm at AAU weather station [40] with 1 minute sampling. The FIT and Gp profiles are fetched from Nordpool [41] for the same period with 1 hour sampling. Due to the speed limits of modbus communication, the measurements: Grid Power and Current (every phase), AC load power (only 3 phase), BESS power, PV power and BESS SOC values are taken with a 4 second sampling time.

The resulting measured PV, load and grid power profiles are shown in Figure 6.7. The grid power is solely the sum of the produced PV power and the load demand at every point in time. As the PV power is producing surplus energy almost all through the examined period, the household is pushing energy to the grid.

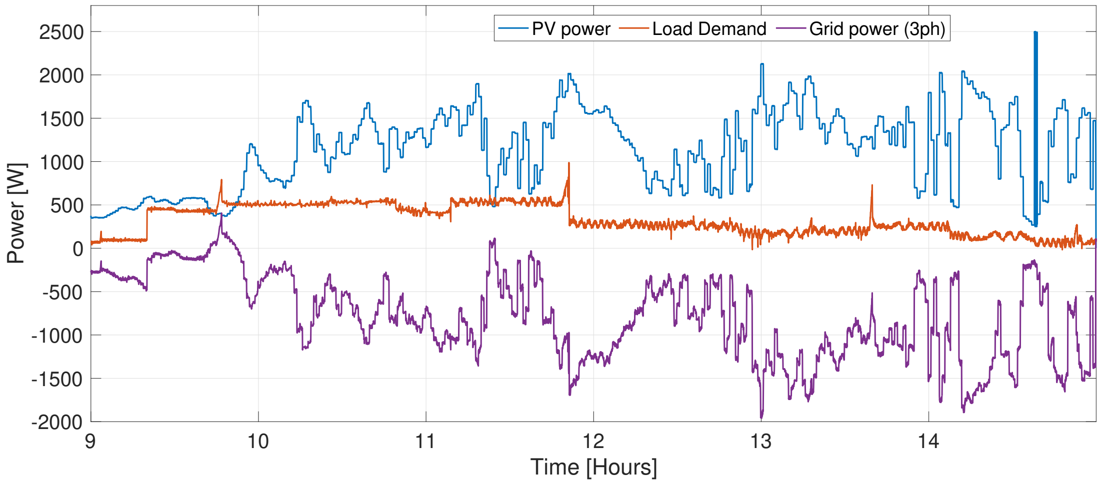

Figure 6.7: Measured Powers for Base Case

The resulting grid cost by the end of the period is -2.674 DKK, meaning it is receiving money for the sold energy.

6.3 Day ahead Schedule

As the input profiles (and the forecast) for the 6 hour period is the same for the two approaches and they utilize the same parameters for both levels, the day-ahead schedule is mutual. The input parameters for the EMS can be seen in Table 6.2.

Table 6.2: EMS input parameters for laboratory test

Variable	Value	Unit
Rated battery energy	6.4/1	kWh/pu
Maximum SOC, SOC_{max}	5.76/0.8	kWh/pu
Minimum SOC, SOC_{min}	1.28/0.2	kWh/pu
Maximum battery power, P_{bat}^{max}	3	kW
Maximum grid current (sum of all phases), I_{grid}^{max}	22	A
Initial state, SOC_{init}	3.328/0.52	kWh/pu
Final state, SOC_{end}	5.12/0.8	kWh/pu
δSOC_1	0.01	-
Δt_1	15	min
δSOC^2	0.001	-
t_2	5	min

The maximum SOC value is a constrained by the actual battery itself. This setting is a built-in and cannot be changed. The reason for using the same parameters for both approaches is to set up the same frame for the laboratory tests. This way the results are only influenced by the implemented dispatcher strategy and can be analyzed better. The day-ahead schedule produced by the first level of the EMS can be seen in Figure 6.8.

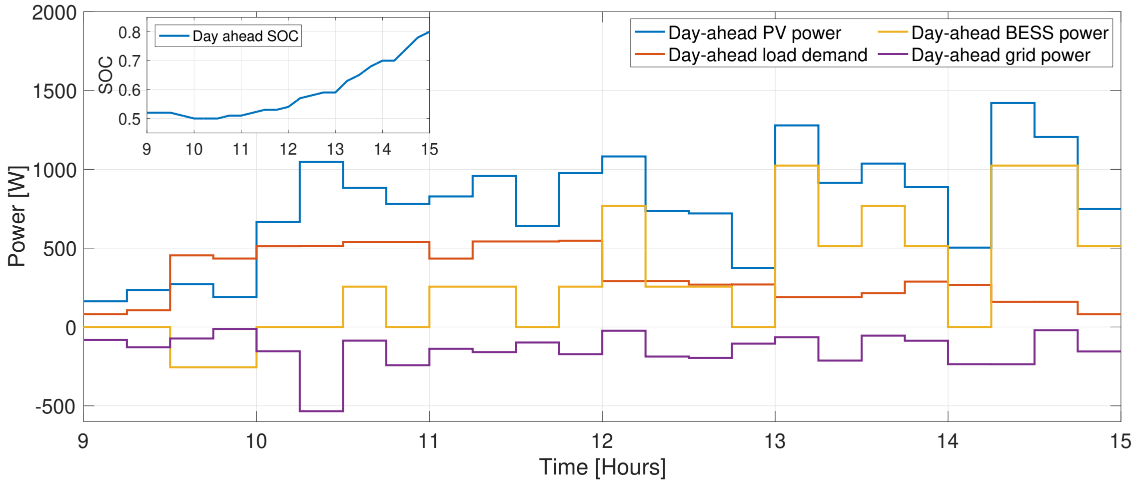

Figure 6.8: Day Ahead Power Schedule for laboratory setup

6.4 Case A: SOC reference

As mentioned in Section 6.2 the sampling time was selected as 4 seconds. This means that the second level has to be conducted every 5 minute under 4 seconds in order to provide sufficient results and power references. This was successfully done, as the new references were in line with the previous one and had not produced any time lag. The resulted power profiles are depicted in Figure 6.9.

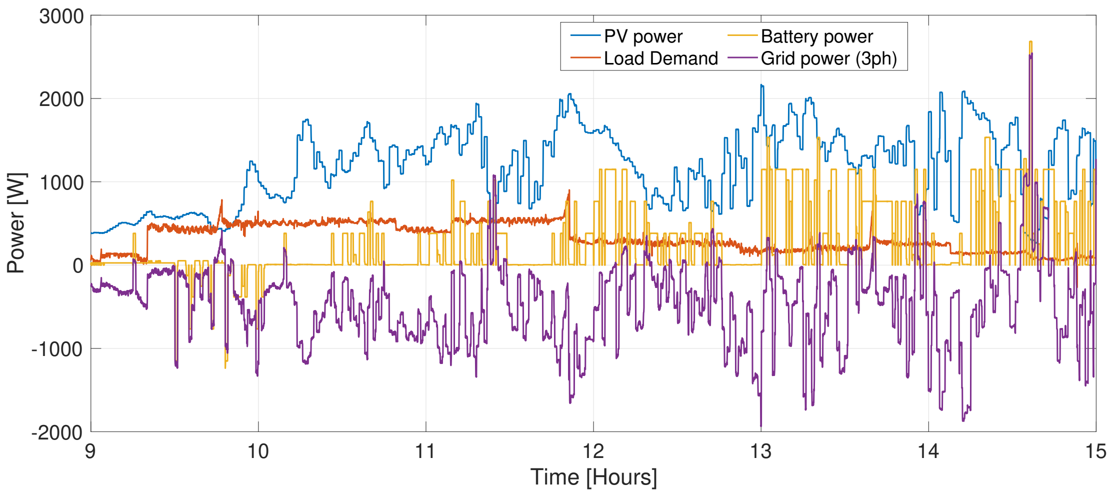

Figure 6.9: Measured Power for SOC reference approach in laboratory setup

The measured load values follow the reference load with some noise, while the PV power fluctuates a lot. The BESS changes output frequently following the second level's dispatcher schedule. To be able to see the exact differences between the day-ahead (first level) and dispatcher's (second level) BESS schedule, Figure 6.10 shows both of them along with the measured battery power and corresponding

SOC profiles.

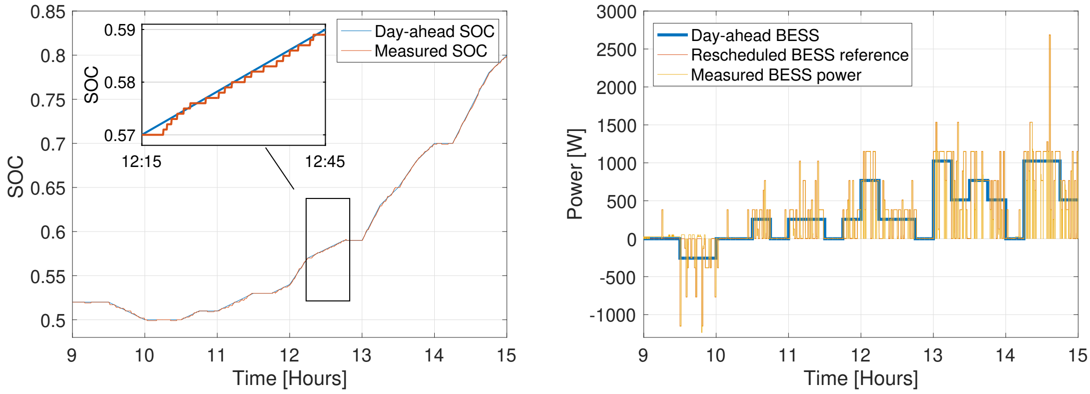

Figure 6.10: BESS power and SOC profiles

Notice that the measured SOC values show the exact same behaviour as it was expected and seen in the results of Section 5.6.1. This proves the effectiveness of the algorithm. It was able to reschedule the BESS based on short term forecast and measurements of real-time values producing the small ripples seen in the picture. It also proves the accuracy of the BESS and inverter model utilized in previous chapters. The battery follows the given references with minor errors of 3-4 W, that could also be a measurement error. The resultant grid power profile is captured in Figure 6.11 along with the original day-ahead grid power.

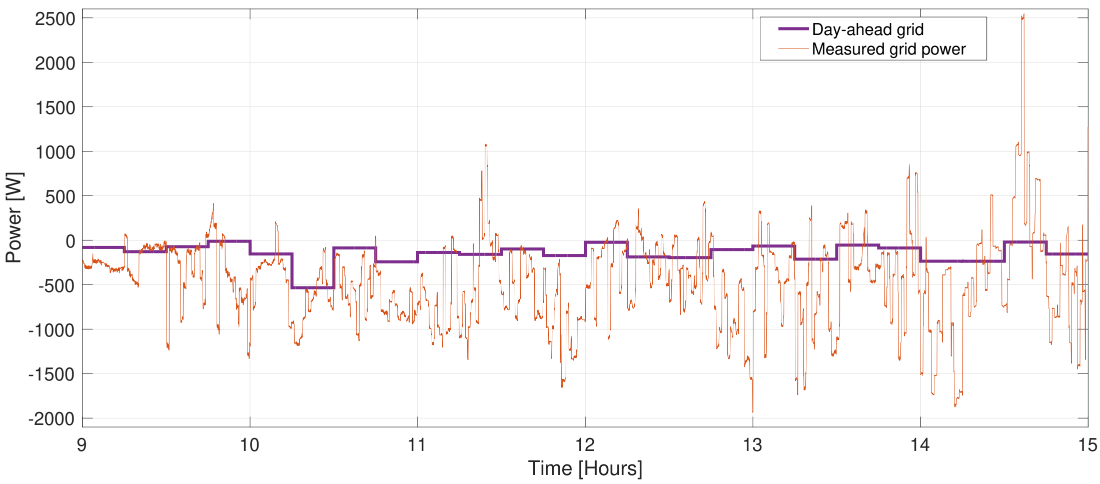

Figure 6.11: Day ahead and actual grid power

The grid power is mainly negative as it was anticipated due to the large amount of PV power. Nevertheless, the household consumes some energy from the grid during the examined period. For instance, just before 10am the load demand peaks, while the PV profile has a dip. This was caught by the EMS at the next rescheduling point and compensated by a discharge from the battery. The other grid peaks (between 11-12 and 14-15) were mainly due to valleys in the PV production as the battery continued to charge as the SOC reference had to be met. The costs associated with the measured power profiles can be seen in Table 6.3 along with the day-ahead costs.

Table 6.3: Day-ahead and actual costs in DKK for the examined period

	Battery degradation	Grid cost	Overall
Base Case	-	-2.674	-2.674
Day-ahead	0.4892	-0.5069	-0.0176
Actual	0.5412	-1.1074	-0.5661

On one hand, the active rescheduling has yielded in a 10% increase in degradation cost compared to the calculated one from the day-ahead profile. On the other hand, the grid cost has been reduced by 118% which is caused by the base effect and absolute numbers tell more information here. The reduced prices are partly because of the underestimated PV power. This underestimation can be seen even more clearly on the base case price which is the highest yield. Nonetheless, the battery was charged with 28% which can be used at other times, making the comparison between the two cases in terms costs complicated.

6.5 Case B: Grid Power reference

Here, the same set up, with the same inputs has been used but the dispatcher strategy has been changed and the P_{grid} reference was utilized. To be able to see full results, a minor change had to be implemented. This test was conducted with $SOC_{init} = 0.4$ and $SOC_{end} = 0.68$. With these settings the absolute SOC difference remains the same, meaning the produced first level schedule stays the same in terms of power profiles, but the SOC schedule has been shifted with 0.12.

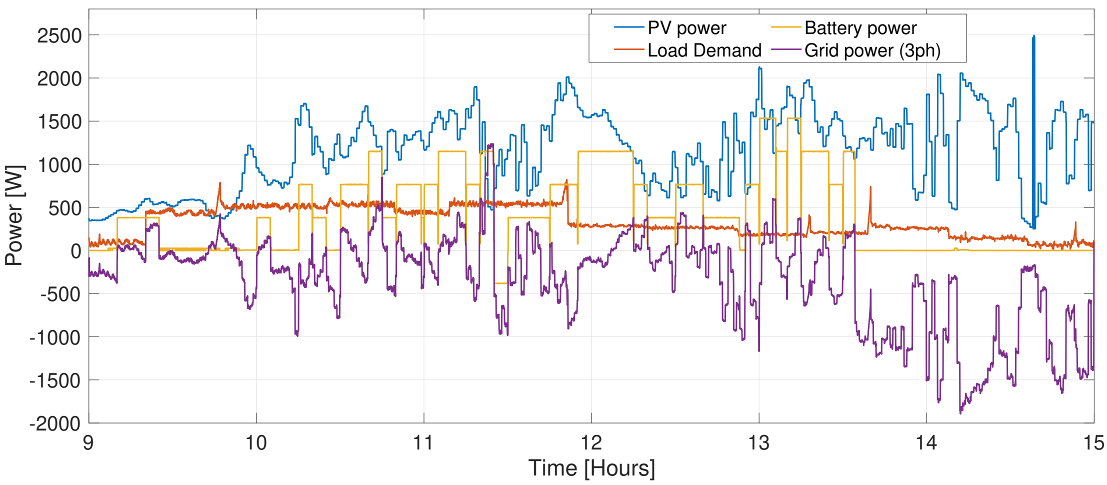

Figure 6.12: Measured Power for grid power deviance minimization approach in laboratory setup

The change was necessary in order to provide the battery enough flexibility before it reaches SOC_{max} due to the anticipated longer charging periods. The resulted power profiles are depicted in Figure 6.12.

The most clear difference is the battery profile. It is being charged even in the beginning as opposed to the previous test and keeps charging the battery more often as there are more PV power available. This trend only breaks once around 11:20, where solar power has a bigger dip and its being compensated by the battery to keep the grid profile close to the reference. Again, the BESS characteristics are depicted in Figure 6.13 to see the effect of the dispatcher strategy.

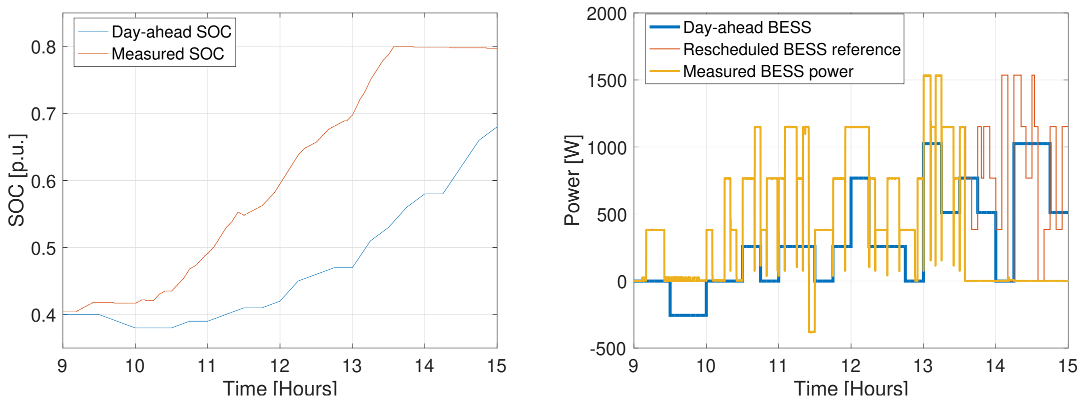

Figure 6.13: BESS power and SOC profiles

The effect of the first charging period can be spotted right away as the SOC profile starts deviating from the day-ahead one just after the beginning. Basically the surplus PV energy is consumed by the battery in order to regulate the grid power. As higher consumption would yield in negative SOC deviation (see results in Table 5.14), excess production results in positive SOC deviation from the scheduled one. The battery reaches its allowable full capacity around 13:35.

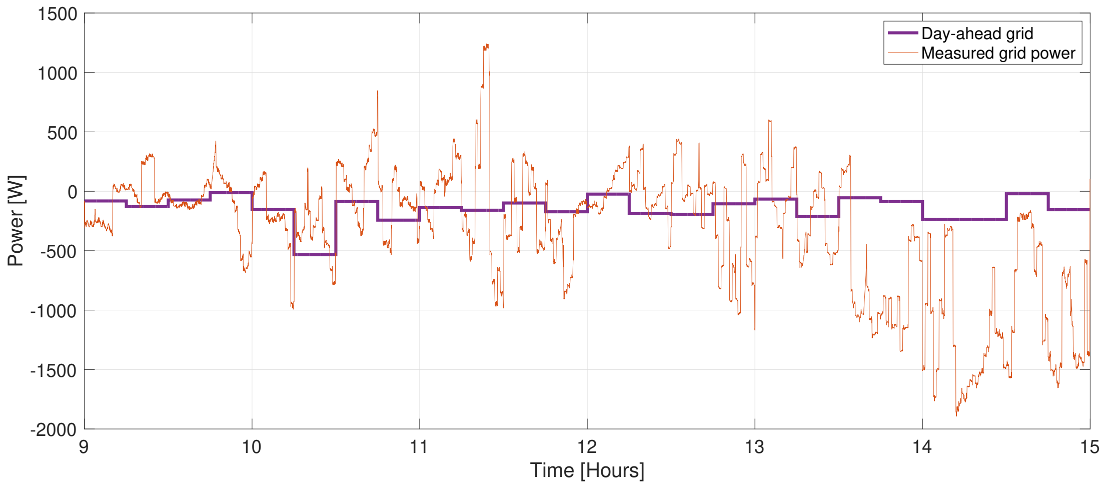

Figure 6.14: Day ahead and actual grid power for grid power deviance minimization approach

After this point the BESS stops charging despite the new references from the EMS. By the end of the examined period the battery managed to charge 40% which is a significant amount. Figure 6.14 shows the reference grid power (calculated from day-ahead schedule) and the measured one. The measured grid power mainly deviates around the reference, having some peaks and dips by the battery and PV. It is clear from the plot that after the battery is fully charged, it loses its regulatory role and the grid power is again only influenced by the load and the PV. To quantify the difference between the reference and the actual one, RMSE of the two profile has been calculated for both approaches for the full 6 hour period, Table 6.4 lists the results.

Table 6.4: RMSE values for the two methods

	Approach with SOC reference	Approach with P_{grid} reference
RMSE [W]:	686.3667	635.5180

RMSE values show that the P_{grid} reference is providing a slightly less deviating grid power profile. If only the time period where the battery was able to act is taken into account (up until around 13:35) the RMSE value drops down to 356 W. It is a significant improvement compared to the 652 W, which is the RMSE for the other approach if it is only calculated for the same period (until 13:35). As long as the battery is available the grid power reference is producing better results in terms of deviation. However, when the battery cannot act anymore, the grid power deviates even more. While it is not able to follow a predefined SOC profile, it is more actively altering the actual power exchange between the household and the grid. The costs associated with the measured power profiles and the defined prices can be seen in Table 6.5 along with the day-ahead costs.

Table 6.5: Day-ahead and actual costs in DKK for the examined period

	Battery degradation	Grid cost	Overall
Base Case	-	-2.674	-2.674
Day-ahead	0.4892	-0.5069	-0.0176
Actual	0.9388	-0.4774	0.4613

The effects of longer charging periods can be seen on the prices as well. The degradation cost almost doubled compared to the SOC reference approach. The grid cost has been also increased due to the smaller amount of sold energy. Overall it finished the period with around 1 DKK more then the other approach and 2 more than the base case. Moreover, in this scenario the prosumers income does not out weight the increased degradation and grid costs and yields in positive actual cost. Nevertheless, the battery managed to accumulate far more energy during the same period (namely 40%), which could provide wider flexibility outside of the examined period and can't be financially quantified in this test.

6.6 Summary

Using the laboratory setup to emulate a realistic scenario has proved the actual feasibility of the proposed EMS. Not only that the algorithm is able to perform the tasks in the required time frame, it is effectively giving out references for the BESS to follow and continuously monitors the whole system. The prosumer can choose between strategies to select the one which best satisfies its needs. By selecting the desired final SOC and dispatch strategy, the prosumer can decide whether a firm SOC path or a stable grid power profile is more beneficial for them. Setting the SOC references restricts the battery, however, it ensures the desired final SOC. On the other hand, minimizing the deviation from the day ahead grid power requires higher flexibility from the battery but it does not guarantee to reach the desired end of the day SOC. The tests showed that the developed EMS is indeed capable of acting without supervision and can execute tasks in real time.

7 Conclusion and Future work

Global energy trends show promising integration of renewables in the upcoming future. Today's green transition in the energy sector cannot be done without involving the demand side i.e. the consumers themselves. It comes with the installation of small scale energy production, the very idea of prosumers. But increasing production on the low voltage side of power grids won't necessarily be a successful idea.

Wide spread electrification of sectors which are traditionally using different types of energy like transportation or heating, are contributing to the consumption. While both demand and supply are undergoing substantial changes in the low voltage grids, there is a missing key piece in the puzzle. Without proper energy management, RES production or the usage of EVs will not serve as a solution, but instead in the short term they can lead to even more problems. The high volatility of RES combined with the periodic peak demands of EV charging, raise a challenge for prosumers and DSOs. On one hand, prosumers cannot experience the benefits of their investments if they cannot minimize their grid dependence. On the other hand, large peaks or unpredictable power demands and even directions are undesirable for the DSO. EMS serves as a solution for the prosumer, by efficiently scheduling its power flows, with the objective of power bill minimization. Moreover, creating a balanced, stable and predictable consumption profile which also ensures grid compliance, can be also advantageous for the DSO. Such a system can incorporate weather forecasts, dynamic electricity prices, driving habits, heat demands, seasonality, etc.

The main objective of this thesis was to design an EMS for a typical household in rural Denmark that is flexible to incorporate wide ranges of assets. The main goal of a successful EMS is to optimally and effectively schedule power flows depending on the uncertainties in the weather forecast, charging needs of EV and dynamic electricity prices. The EMS has to be able to actually manage the instantaneous power flows on a minute level, while still holding all the grid or user defined constraints. To tackle this goal, a two level DP based optimization has been implemented and tested in various circumstances. First, a long term analyses has been conducted with different asset sizes to prove the financial benefits of the proposed EMS. Second, the dispatcher algorithm has been put in a simulation environment to inspect the effect of separate parameters on the effectiveness of EMS under realistic conditions. Furthermore, these cases showed the importance and effectiveness of short term statistics based forecast in EMS applications. Third, a laboratory validation has been conducted to fully prove its feasibility on actual hardware.

The main challenges which were encountered and tackled throughout this process are listed below:

- To propose a fitting optimization technique for power scheduling in EMS.
- To apply and fit the selected optimization technique to the chosen problem.
- To propose a method to quantify the BESS degradation in order to protect the BESS from premature aging and integrate it in the EMS algorithm.
- To prove that the proposed EMS is capable of effective energy management and yields in financial gains on the long run.
- To successfully develop a second level for the EMS which manages the power flows on a minute level.
- To incorporate short term weather forecast in order to consider the uncertainties in the weather encountered during real-time operation and dispatch.
- To test the developed algorithm in a laboratory set up demonstrating its feasibility and practicality.

Based on the work done, the following remarks can be stated:

- EMS when properly optimized can enable a prosumer to drastically minimize the electricity bill.
- Accounting for the dynamic electricity prices while charging the EV is one of the most important aspects of an effective EMS.
- It is important to protect the BESS from premature aging by considering the degradation costs and limiting its maximum and minimum permissible SOC level, as BESS is one of the most crucial and expensive asset of the EMS.
- It is essential for a well functioning EMS to adjust its schedule depending on the actual available RES and load demand. Their volatility makes it challenging to schedule the BESS properly. Active measurements and short term forecast are greatly enhancing the efficiency of the system.
- Just using the right parameters for the algorithm can have a substantial impact on the results. Therefore, their careful selection is crucial for an optimally operating EMS.
- The laboratory run validates the results obtained from the simulations performed for developing the DP based EMS. The EMS proved to be efficient in terms of reducing electricity cost, scheduling the BESS and adjusting its schedules based on the uncertainties in RES (PV in case of laboratory setup) production.

The objectives defined in the beginning has been fully achieved. A functional and effective DP based EMS for household prosumers has been constructed, tested and proved to be feasible in a laboratory setup.

Future Work

To further enhance the proposed EMS solution and benefit prosumers even more, a number of improvements could be made. These could be either minor extensions like:

- Developing reactive power management, which also accounts for the reactive power demands of the household and the increased current load caused by that.
- Further analyse the effects of parameters like δSOC and Δt.
- Conduct wider variety of tests, including various weather and load scenarios.
- Develop a method to optimize end of the day SOC values and update them during execution based on actual measurements and short term forecast.

While major upgrades would consist in:

- Taking into account power quality aspects (unbalanced phases, harmonics, $cos(\phi)$, flicker, etc...) to further improve the benefits both for the prosumer and the DSO.
- Include loads which can be scheduled to widen the range of flexibility in the system and maximize effectiveness of optimization.
- Implement better load forecast (ANN for example) based on the specific individual household.
- Include site specific weather forecast which automatically updates and provides data for the first level (day-ahead scheduling).
- Utilize cloud networks to store data of measurements for analysis and forecast.

By solving the above mentioned challenges, an innovative, flexible and effective tool would be created to put in use for variety of prosumers. Sophisticated softwares are key to green future and efficient energy management.

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A Yearly input data and results

A.1 Data

Grid Prices and Feed-In-Tariff

The hourly Grid Prices (Gp) and the Feed-In-Tariff (FIT) for the whole year (2018) were fetched from the Nordpool [41]. Figure A.1 shows the profiles.

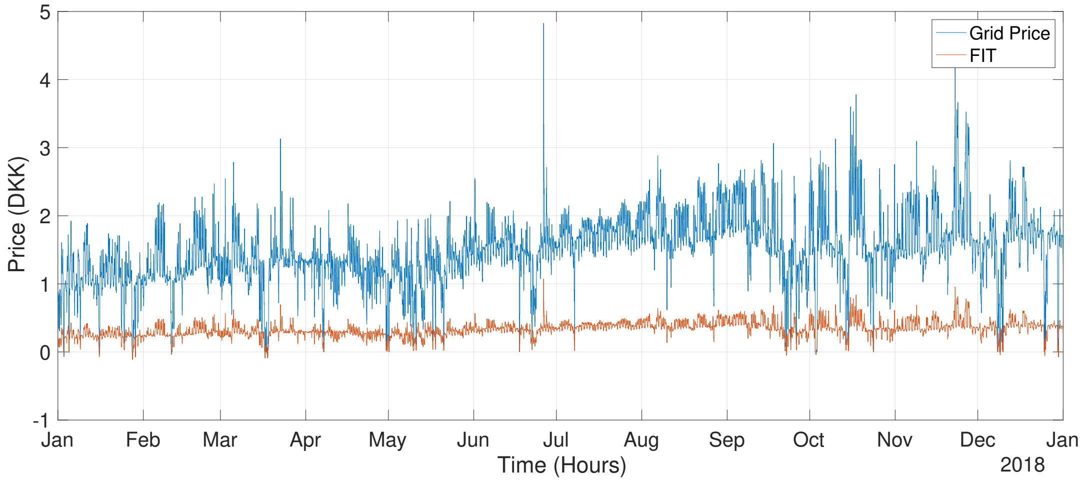

Figure A.1: Gp and FIT from Nordpool [41]

PV Production

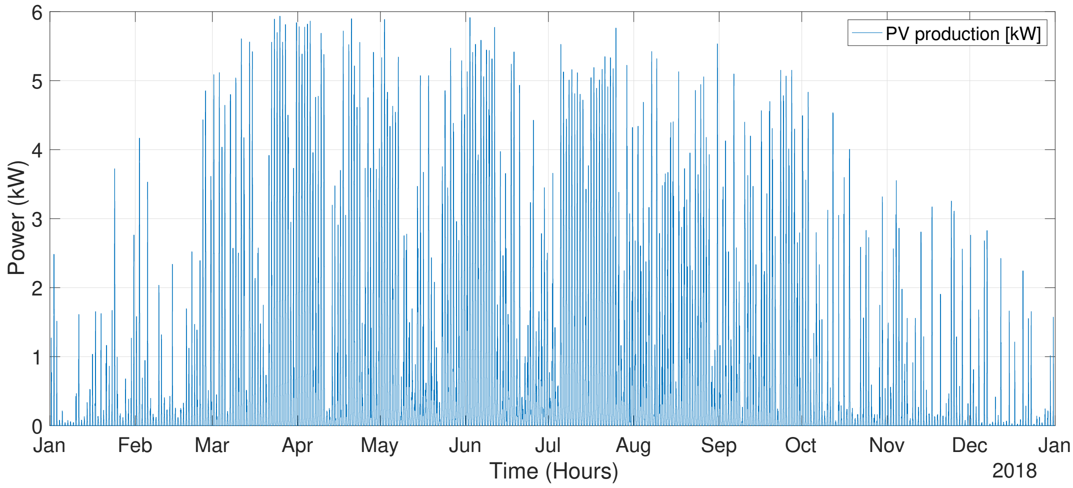

Figure A.2: PV Production (2018)

The hourly PV production incurred at the household is shown in Figure A.2. The profile was obtained from the weather station located at AAU for an entire year (2018) [40].

Electrical Load Demand

The hourly electrical load demand at the household is shown in Figure A.3. The profile was obtained from Aalborg University.

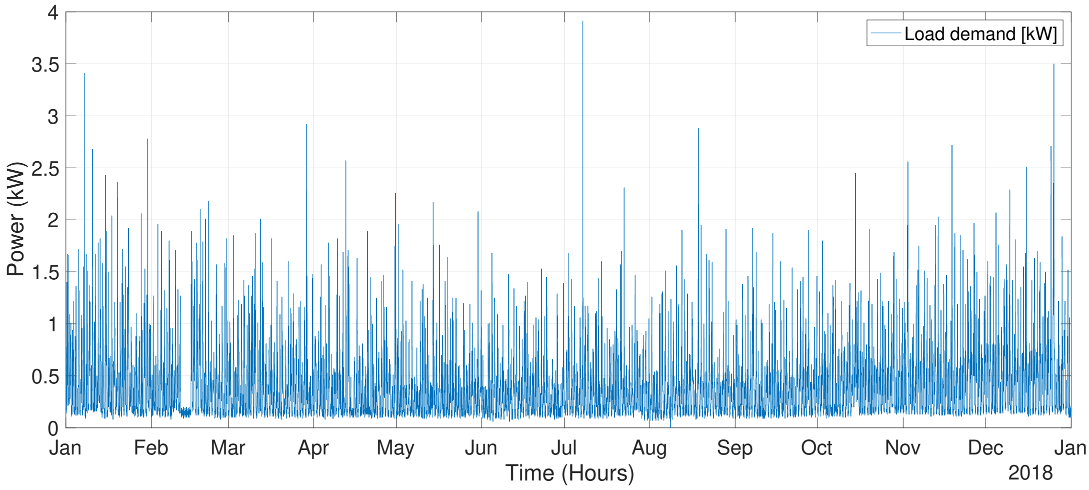

Figure A.3: Electrical Load Demand at the House (2018)

Small Wind Turbine Power Production

The hourly production from the Small Wind Turbine (SWT) at the household is shown in Figure A.4. The profile for the wind speed was obtained from AAU weather station [40]. The Power from the given wind speed was obtained with the help of a look-up table as described in Section 3.1.1.

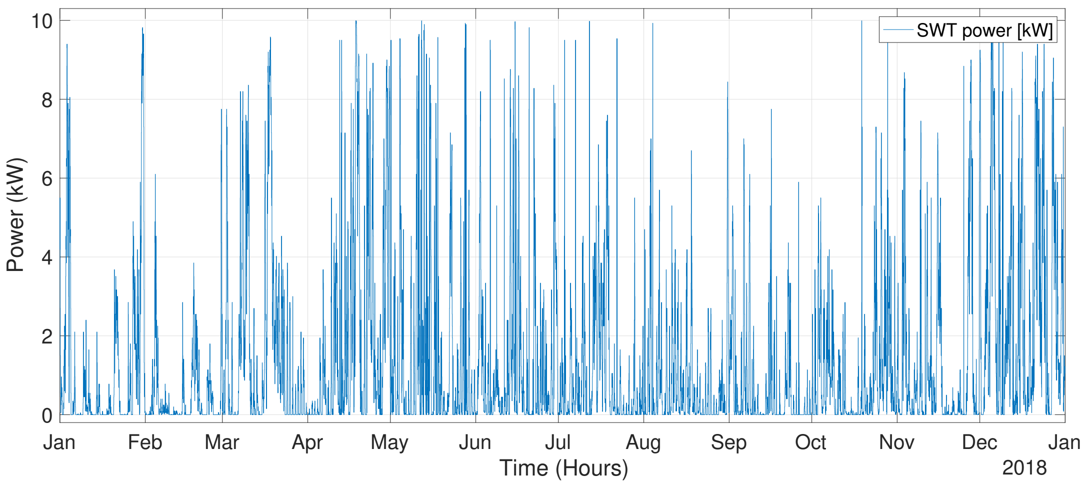

Figure A.4: Power from the Small Wind Turbine (2018)

Heat Demand

The hourly heat demand from the Heat Pump (HP) at the household is shown in Figure A.5. The profile for the heat demand of the household was obtained from Aalborg University. The given heat demand was converted into the electrical demand using the Coefficient of Power (COP) value as described in Section 3.1.3.

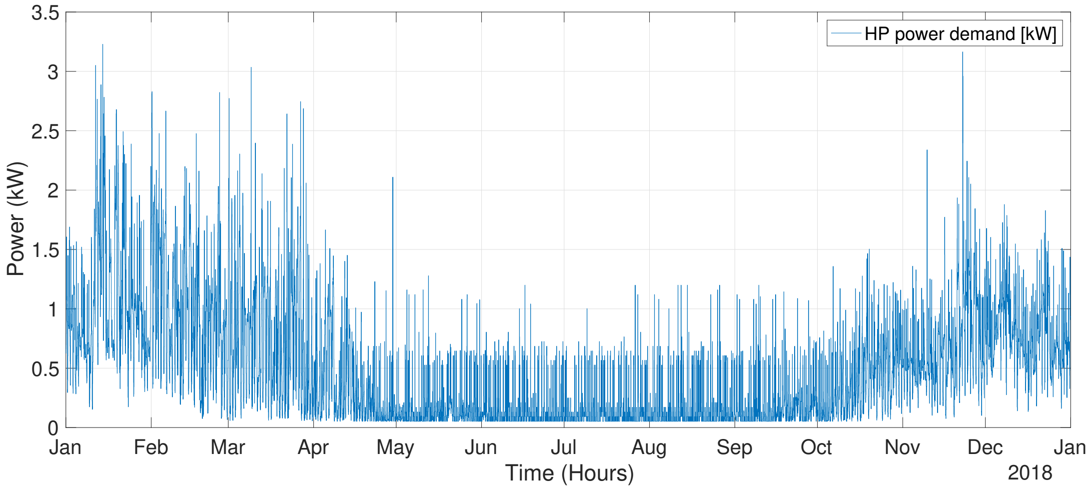

Figure A.5: Heat Demand at the Household (2018)

A.2 Example power profiles for long term analysis

Some examples of the power profiles of the yearly analysis as a result of DP based EMS are shown in Figures A.6, A.7, A.8, A.9. All these examples are using the parameters from Table 4.3 for the BESS. For the Electrical Vehicle (EV) Hyundai Kona is shown in Figure A.6.

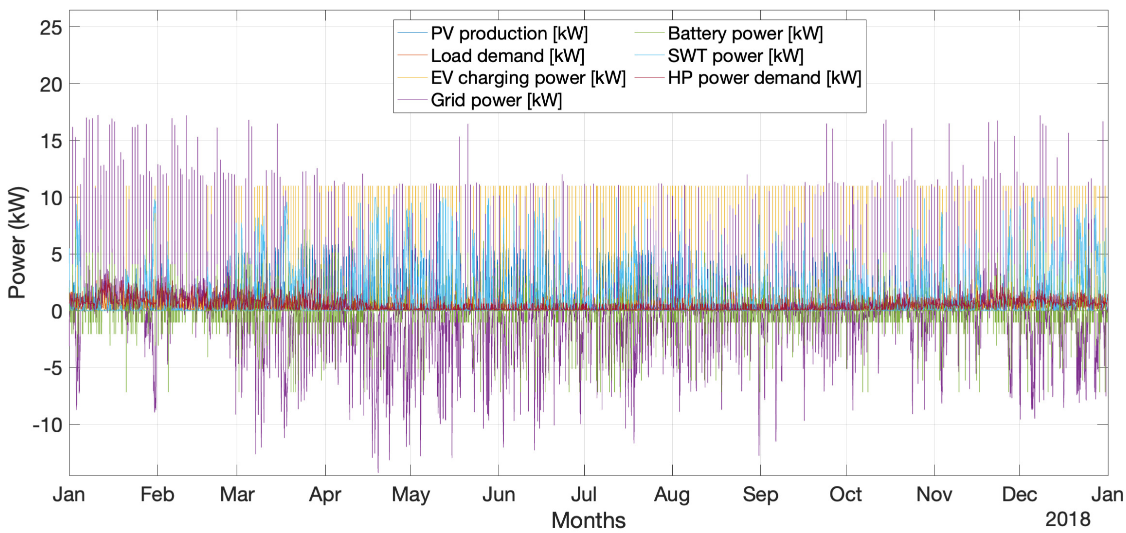

Figure A.6: Yearly Power Schedule: Hyundai Kona

The yearly schedule as a result of DP based EMS for the EV Nissan Leaf is shown in Figure A.7.

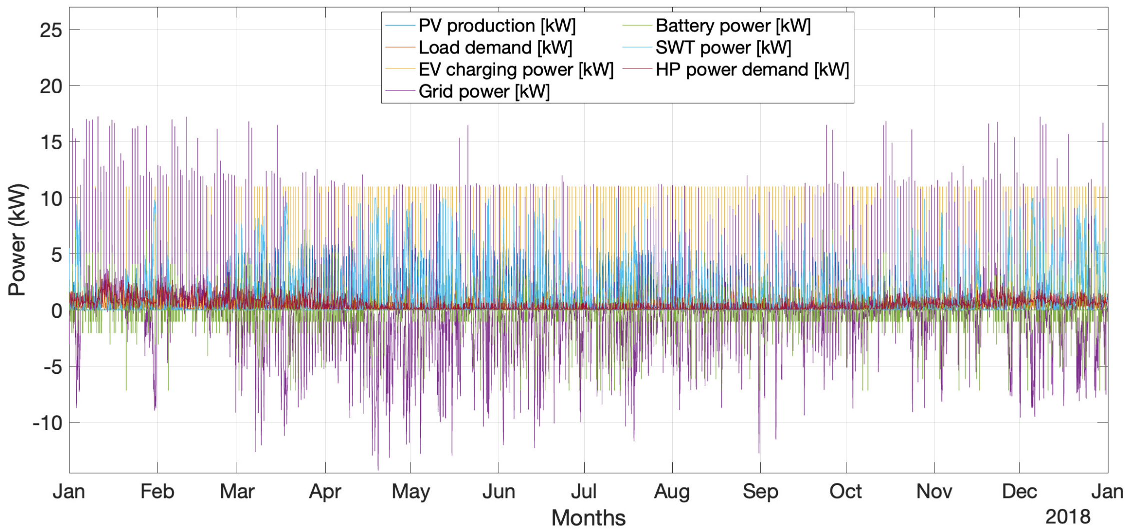

Figure A.7: Yearly Power Schedule: Nissan Leaf

The yearly schedule as a result of DP based EMS for the EV Tesla Model 3 Standard Plus is shown in Figure A.8.

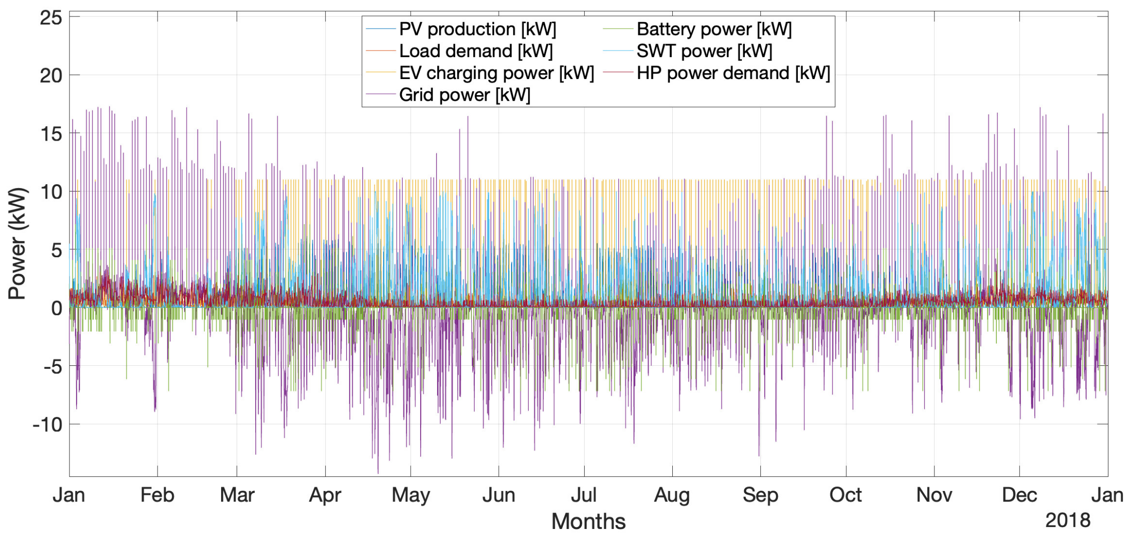

Figure A.8: Yearly Power Schedule: Tesla Model 3 Standard Plus

The yearly schedule as a result of DP based EMS for the EV Audi e-tron 55 quattro is shown in Figure A.9.

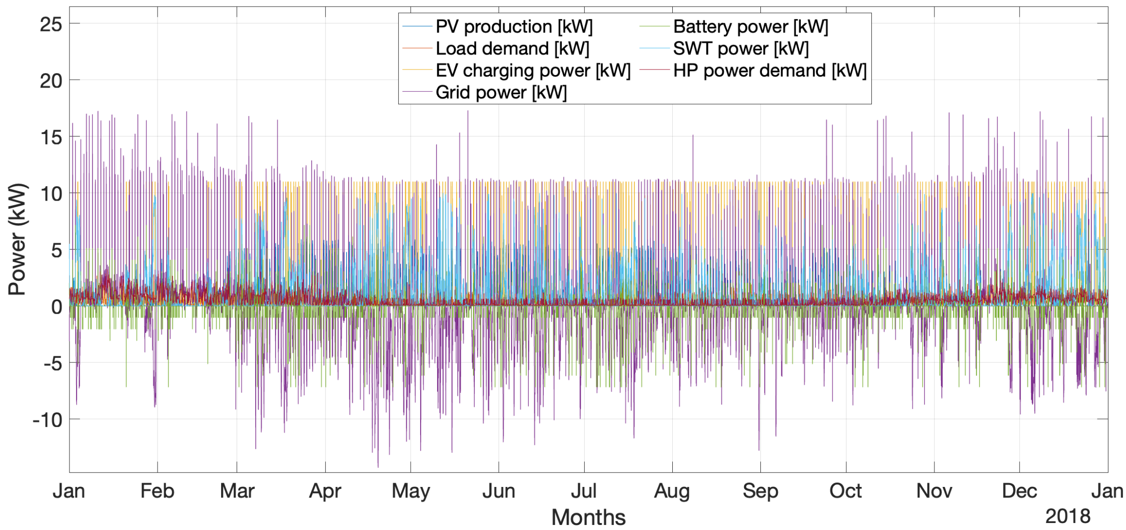

Figure A.9: Yearly Power Schedule: Audi e-tron 55 quattro

B | Cost Analysis

Cost Analysis

The proposed EMS was subjected to four different EV types and different parameters such as BESS sizes and BESS SOC ranges were varied. The exact costs as well as peak grid currents obtained from permutations of possible SOC ranges and BESS sizes are presented in the following sections. δ SOC for all the cases is set to 0.1. In Tables B.1, B.2, B.3 and B.4), each of the four scenarios show the lowest price associated in bold letters.

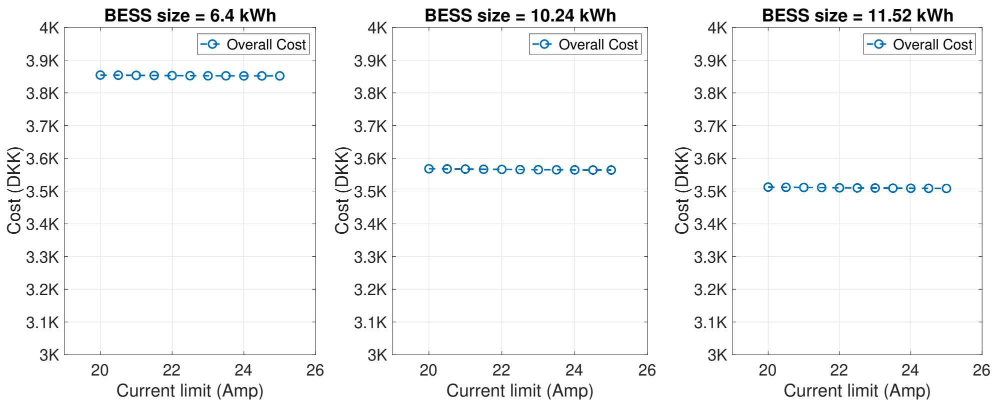

Figure B.1: Costs associated with different current limits : Tesla Model 3 Standard Plus

Cost Analysis: Hyundai Kona

Table B.1: Summary of all Test Scenarios and Prices: **Hyunadai Kona**

Electric Vehicle	Degradation Cost (DKK/yr)	Peak Current (Amp)	Grid Cost (DKK/yr)	Overall Cost (DKK/yr)	SOC Range ↓	SOC Values ↔	BESS Size (kWh)
	285.60	**20.42**	4474.8	4760.4	0.2	0.4-0.6	6.4
	392.34	21.34	4207.0	4599.3	0.3	0.4-0.7	6.4
	488.05	22.26	3968.2	4456.2	0.4	0.4-0.8	6.4
	569.39	23.19	3766.2	4335.6	0.5	0.3-0.8	6.4
	647.37	24.11	3581.1	4228.4	0.6	0.2-0.8	6.4
	717.40	24.80	3414.5	4131.9	0.7	0.2-0.9	6.4
	777.03	24.88	3268.3	4045.4	0.8	0.1-0.9	6.4
	831.77	24.88	3135.4	3967.2	0.9	0.1-1.0	6.4
	884.37	24.88	**3011.0**	**3895.3**	1.0	0.0-1.0	6.4
	369.4	**21.52**	4225.7	4595.1	0.2	0.4-0.6	10.24
	503.94	23.00	3885.6	4389.5	0.3	0.4-0.7	10.24
	618.93	24.48	3599.6	4218.6	0.4	0.4-0.8	10.24
Hyundai Kona	713.50	24.88	3360.9	4074.4	0.5	0.3-0.8	10.24
	789.87	24.88	3162.3	3952.2	0.6	0.2-0.8	10.24
	860.47	24.88	2985.1	3845.6	0.7	0.2-0.9	10.24
	918.19	24.88	2842.6	3760.8	0.8	0.1-0.9	10.24
	968.80	24.88	2715.0	3683.8	0.9	0.1-1.0	10.24
	1011.0	24.88	**2605.1**	**3616.5**	1.0	0.0-1.0	10.24
	395.05	**21.89**	4161.7	4556.7	0.2	0.4-0.6	11.52
	538.08	23.56	3805.6	4343.7	0.3	0.4-0.7	11.52
	652.50	24.99	3516.4	4168.9	0.4	0.4-0.8	11.52
	750.15	24.99	3268.5	4018.6	0.5	0.3-0.8	11.52
	831.04	24.99	3062.0	3893.1	0.6	0.2-0.8	11.52
	897.60	24.99	2894.3	3791.9	0.7	0.2-0.9	11.52
	952.86	24.99	2755.5	3708.3	0.8	0.1-0.9	11.52
	999.71	24.88	2637.3	3637.0	0.9	0.1-1.0	11.52
	1040.2	24.88	**2530.0**	**3570.1**	1.0	0.0-1.0	11.52

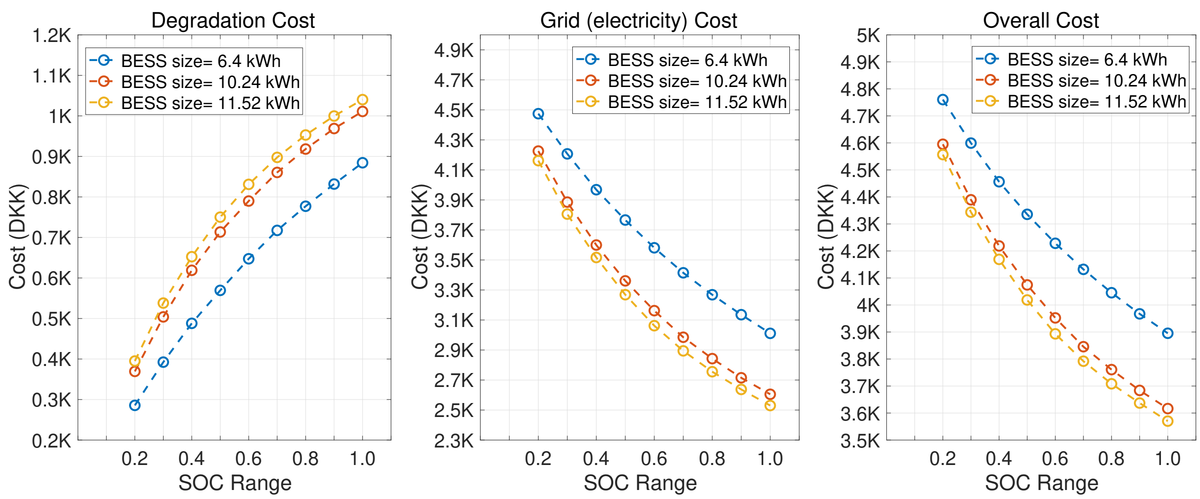

Figure B.2: (a) Degradation Cost (b) Grid Cost (c) Overall Cost for Hyundai Kona

Cost Analysis: Nissan leaf

Table B.2: Summary of all Test Scenarios and Prices: **Nissan Leaf**

Electric Vehicle	Degradation Cost (DKK/yr)	Peak Current (Amp)	Grid Cost (DKK/yr)	Overall Cost (DKK/yr)	SOC Range ↓	SOC Values ↔	BESS Size (kWh)
	287.14	**20.42**	4571.9	4859.0	0.2	0.4-0.6	6.4
	392.34	21.34	4307.4	4699.7	0.3	0.4-0.7	6.4
	487.13	22.26	4071.5	4558.6	0.4	0.4-0.8	6.4
	567.56	23.19	3870.5	4438.0	0.5	0.3-0.8	6.4
	642.48	24.11	3689.0	4331.5	0.6	0.2-0.8	6.4
	711.90	24.80	3524.4	4236.3	0.7	0.2-0.9	6.4
	771.83	24.88	3378.5	4150.3	0.8	0.1-0.9	6.4
	824.74	24.88	3247.0	4071.7	0.9	0.1-1.0	6.4
	878.86	24.88	**3120.5**	**3999.4**	1.0	0.0-1.0	6.4
	368.96	**21.52**	4325.5	4694.4	0.2	0.4-0.6	10.24
	501.27	23.00	3990.4	4491.7	0.3	0.4-0.7	10.24
	613.60	24.48	3707.4	4321.0	0.4	0.4-0.8	10.24
Nissan Leaf	709.95	24.88	3466.1	4176.1	0.5	0.3-0.8	10.24
	788.10	24.88	3265.2	4053.3	0.6	0.2-0.8	10.24
	856.03	24.88	3091.6	3947.7	0.7	0.2-0.9	10.24
	914.19	24.88	2948.3	3862.5	0.8	0.1-0.9	10.24
	963.92	24.88	2822.2	3786.1	0.9	0.1-1.0	10.24
	1007.4	24.88	**2711.3**	**3718.8**	1.0	0.0-1.0	10.24
	392.58	**21.89**	4263.8	4656.4	0.2	0.4-0.6	11.52
	532.16	23.56	3913.2	4445.4	0.3	0.4-0.7	11.52
	650.03	24.99	3620.5	4270.6	0.4	0.4-0.8	11.52
	749.17	24.99	3371.6	4120.7	0.5	0.3-0.8	11.52
	827.58	24.99	3167.9	3995.9	0.6	0.2-0.8	11.52
	895.65	24.99	2998.5	3894.1	0.7	0.2-0.9	11.52
	947.93	24.99	2862.8	3810.7	0.8	0.1-0.9	11.52
	992.31	24.88	2746.9	3739.3	0.9	0.1-1.0	11.52
	1032.8	24.88	**2639.4**	**3672.2**	1.0	0.0-1.0	11.52

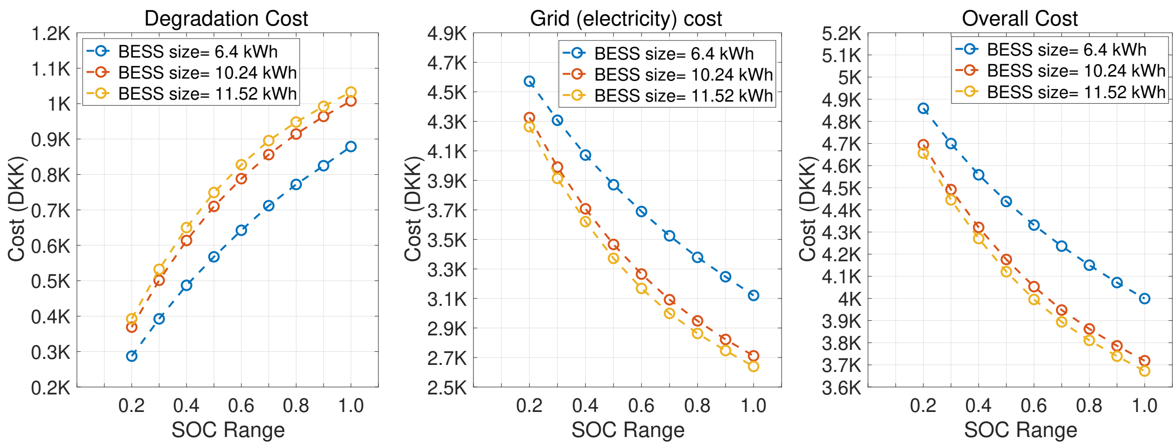

Figure B.3: (a) Degradation Cost (b) Grid Cost (c) Overall Cost for Nissan Leaf

Cost Analysis:Tesla Model 3 Standard Plus

Table B.3: Summary of all Test Scenarios and Prices: **Tesla Model 3 Standard Plus**

Electric Vehicle	Degradation Cost (DKK/yr)	Peak Current (Amp)	Grid Cost (DKK/yr)	Overall Cost (DKK/yr)	SOC Range ↓	SOC Values ↔	BESS Size (kWh)
Tesla Model 3 Standard Plus	**287.45**	**20.66**	4209.3	4496.8	0.2	0.4-0.6	6.4
	400.29	21.58	3930.3	4330.6	0.3	0.4-0.7	6.4
	497.53	22.50	3686.3	4183.9	0.4	0.4-0.8	6.4
	583.16	23.43	3477.6	4060.8	0.5	0.3-0.8	6.4
	659.30	24.35	3290.0	3949.3	0.6	0.2-0.8	6.4
	732.08	24.63	3119.8	3851.9	0.7	0.2-0.9	6.4
	795.80	24.88	2969.5	3764.6	0.8	0.1-0.9	6.4
	849.50	24.88	2837.1	3686.6	0.9	0.1-1.0	6.4
	902.72	24.88	**2713.8**	**3616.6**	1.0	0.0-1.0	6.4
	380.95	**21.77**	3946.2	4327.1	0.2	0.4-0.6	10.24
	515.04	23.24	3602.0	4117.0	0.3	0.4-0.7	10.24
	634.92	24.72	3304.0	3939.0	0.4	0.4-0.8	10.24
	735.26	24.96	3057.9	3793.1	0.5	0.3-0.8	10.24
	810.74	24.96	2859.7	3670.5	0.6	0.2-0.8	10.24
	882.22	24.96	2682.1	3564.3	0.7	0.2-0.9	10.24
	941.28	24.96	2535.5	3476.8	0.8	0.1-0.9	10.24
	994.56	24.96	2404.7	3399.2	0.9	0.1-1.0	10.24
	1037.6	24.96	**2294.6**	**3332.2**	1.0	0.0-1.0	10.24
	408.86	**22.13**	3877.9	4286.8	0.2	0.4-0.6	11.52
	553.3	23.80	3514.2	4067.6	0.3	0.4-0.7	11.52
	675.68	24.81	3211.3	3887.0	0.4	0.4-0.8	11.52
	773.83	24.88	2962.1	3735.9	0.5	0.3-0.8	11.52
	853.23	24.88	2758.3	3611.6	0.6	0.2-0.8	11.52
	920.80	24.96	2682.1	3564.3	0.7	0.2-0.9	11.52
	977.02	24.88	2447.6	3424.6	0.8	0.1-0.9	11.52
	1022.4	24.88	2330.6	**3353.0**	0.9	0.1-1.0	11.52
	1061.4	24.88	**2225.5**	3386.9	1.0	0.0-1.0	11.52

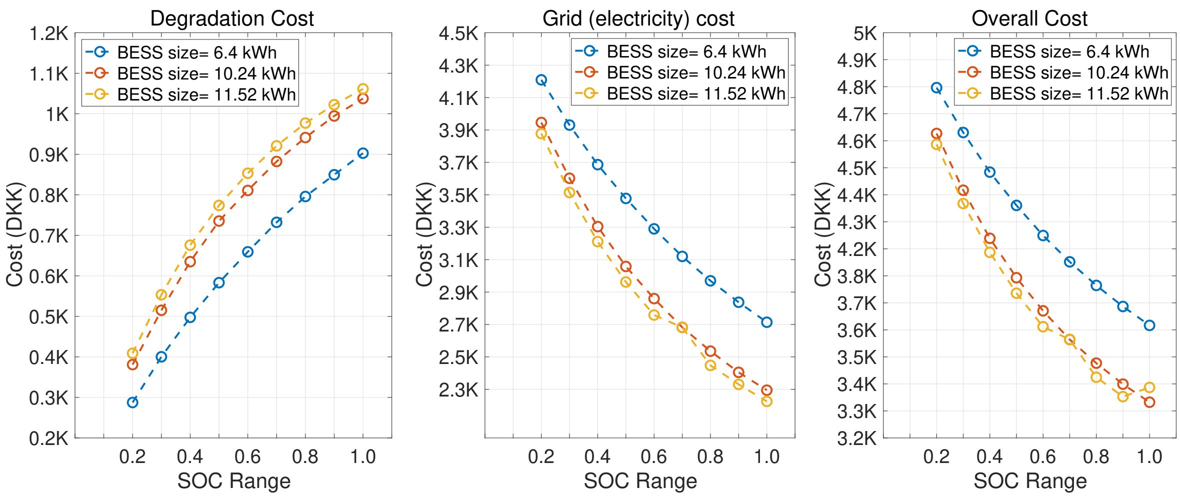

Figure B.4: (a) Degradation Cost (b) Grid Cost (c) Overall Cost for Tesla Model 3

Table B.4: Summary of all Test Scenarios and Prices: **Audi e-tron 55 S quattro**

Electric Vehicle	Degradation Cost (DKK/yr)	Peak Current (Amp)	Grid Cost (DKK/yr)	Overall Cost (DKK/yr)	SOC Range ↓	SOC Values ↔	BESS Size (kWh)
Audi e-tron 55 S quattro	**310.08**	**20.42**	7800.0	8110.4	0.2	0.4-0.6	6.4
	440.35	21.34	7492.5	7932.9	0.3	0.4-0.7	6.4
	558.69	22.26	7212.3	7771.0	0.4	0.4-0.8	6.4
	661.13	23.19	6970.7	7631.8	0.5	0.3-0.8	6.4
	748.29	24.11	6761.4	7509.7	0.6	0.2-0.8	6.4
	830.85	24.80	6568.7	7399.6	0.7	0.2-0.9	6.4
	899.96	24.88	6406.4	7306.4	0.8	0.1-0.9	6.4
	958.07	24.88	6265.2	7223.3	0.9	0.1-1.0	6.4
	1005.2	24.88	**6142.4**	**7147.5**	1.0	0.0-1.0	6.4
	418.69	**21.52**	7503.1	7921.8	0.2	0.4-0.6	10.24
	582.52	23.00	7100.6	7683.1	0.3	0.4-0.7	10.24
	719.28	24.48	6766.1	7485.4	0.4	0.4-0.8	10.24
	825.84	24.88	6497.3	7323.1	0.5	0.3-0.8	10.24
	902.20	24.88	6292.0	7194.2	0.6	0.2-0.8	10.24
	969.69	24.96	6115.0	7084.7	0.7	0.2-0.9	10.24
	1032.7	24.96	5962.4	6995.1	0.8	0.1-0.9	10.24
	1078.5	24.96	5834.2	6912.7	0.9	0.1-1.0	10.24
	1122.4	24.96	**5718.1**	**6840.5**	1.0	0.0-1.0	10.24
	451.27	**21.89**	7421.7	7873.0	0.2	0.4-0.6	11.52
	626.85	23.56	7000.3	7627.2	0.3	0.4-0.7	11.52
	761.50	24.99	6666.1	7427.6	0.4	0.4-0.8	11.52
	864.57	24.99	6400.9	7265.5	0.5	0.3-0.8	11.52
	945.46	24.99	6188.5	7134.0	0.6	0.2-0.8	11.52
	1016.5	24.99	6011.1	7027.6	0.7	0.2-0.9	11.52
	1069.3	24.99	5872.5	6941.8	0.8	0.1-0.9	11.52
	1113.6	24.99	5751.4	6865.0	0.9	0.1-1.0	11.52
	1158.0	24.99	**5632.1**	**6790.2**	1.0	0.0-1.0	11.52

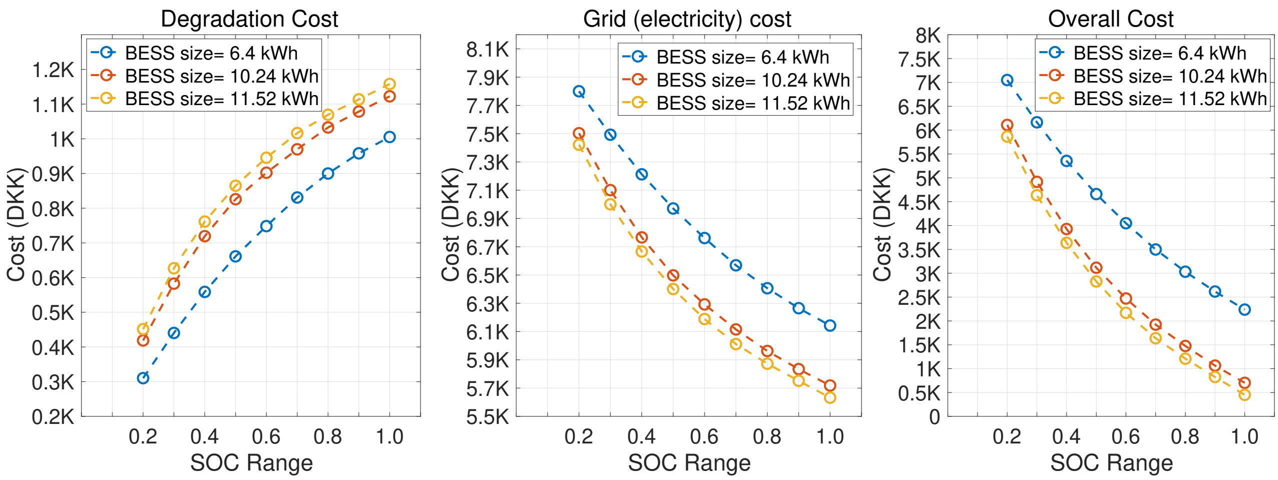

Figure B.5: (a) Degradation Cost (b) Grid Cost (c) Overall Cost for Audi e-tron

C | Fine tuning of historical periods for forecasting horizons

C.1 Variations in Mean Errors with Historical Period (H) for forecasting horizon of 5 minutes

Table C.1: Mean Errors: 5 minutes

H	Difference	RMSE	MAE	MBE
50	0.58	2.32	1.89	1.45
75	0.57	2.30	1.87	1.42
100	0.56	2.30	1.87	1.42
125	0.56	2.31	1.89	1.43
150	0.57	2.32	1.89	1.44
175	0.57	2.30	1.88	1.42
200	0.58	2.30	1.88	1.43
225	0.57	2.29	1.87	1.41
250	0.56	2.30	1.87	1.42
275	0.57	2.31	1.88	1.43
300	0.57	2.31	1.88	1.43
325	0.56	2.31	1.88	1.43
350	0.56	2.31	1.88	1.43

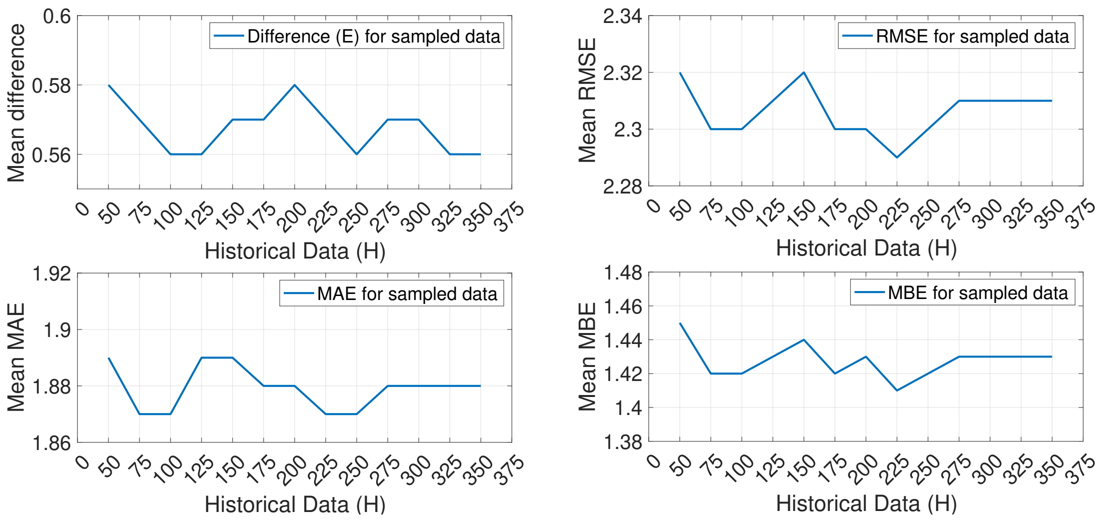

Figure C.1: Variations in Mean Errors with H for forecasting horizon of: 5 minutes

C.2 Variations in Mean Errors with Historical Period (H) for forecasting horizon of 10 minutes

Table C.2: Mean Errors: 10 minutes

H	Difference	RMSE	MAE	MBE
50	0.60	2.30	1.87	1.43
75	0.59	2.30	1.87	1.43
100	0.57	2.27	1.85	1.39
125	0.59	2.30	1.87	1.41
150	0.58	2.30	1.87	1.42
175	0.58	2.30	1.87	1.42
200	0.59	2.29	1.87	1.42
225	0.58	2.29	1.87	1.41
250	0.58	2.30	1.88	1.43
275	0.58	2.30	1.88	1.43
300	0.58	2.30	1.88	1.43
325	0.58	2.30	1.88	1.43
350	0.58	2.30	1.88	1.43

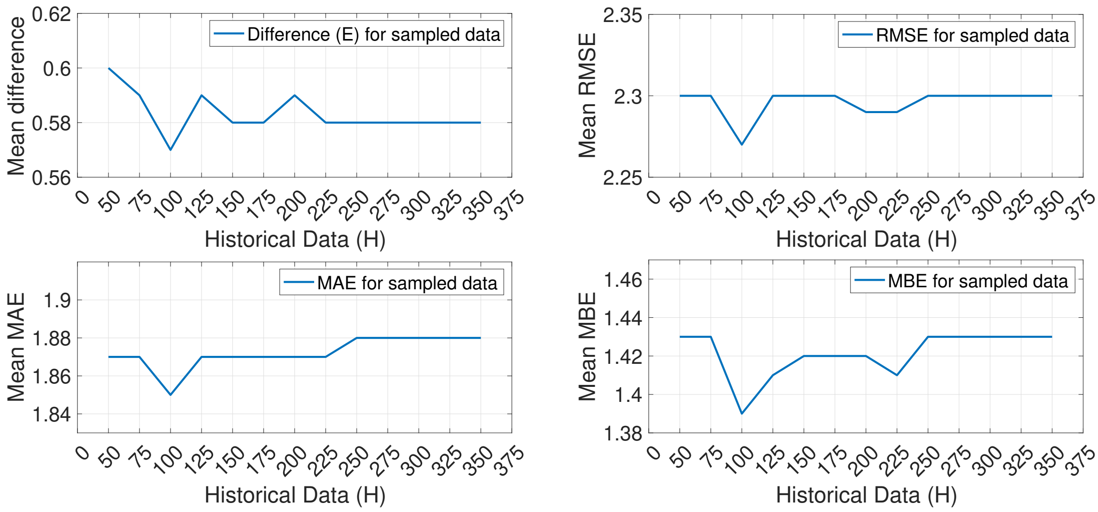

Figure C.2: Variations in Mean Errors with H for forecasting horizon of: 10 minutes

C.3 Variations in Mean Errors with Historical Period (H) for forecasting horizon of 15 minutes

Table C.3: Mean Errors: 15 minutes

H	Difference	RMSE	MAE	MBE
50	0.70	2.35	1.92	1.49
100	0.65	2.31	1.89	1.43
150	0.66	2.32	1.90	1.44
200	0.67	2.30	1.88	1.42
250	0.63	2.28	1.86	1.39
300	0.64	2.31	1.89	1.44
350	0.65	2.31	1.89	1.43
400	0.64	2.31	1.88	1.43
450	0.65	2.31	1.89	1.44
500	0.64	2.32	1.89	1.44
550	0.64	2.32	1.89	1.44
600	0.64	2.32	1.89	1.44
650	0.64	2.32	1.89	1.45

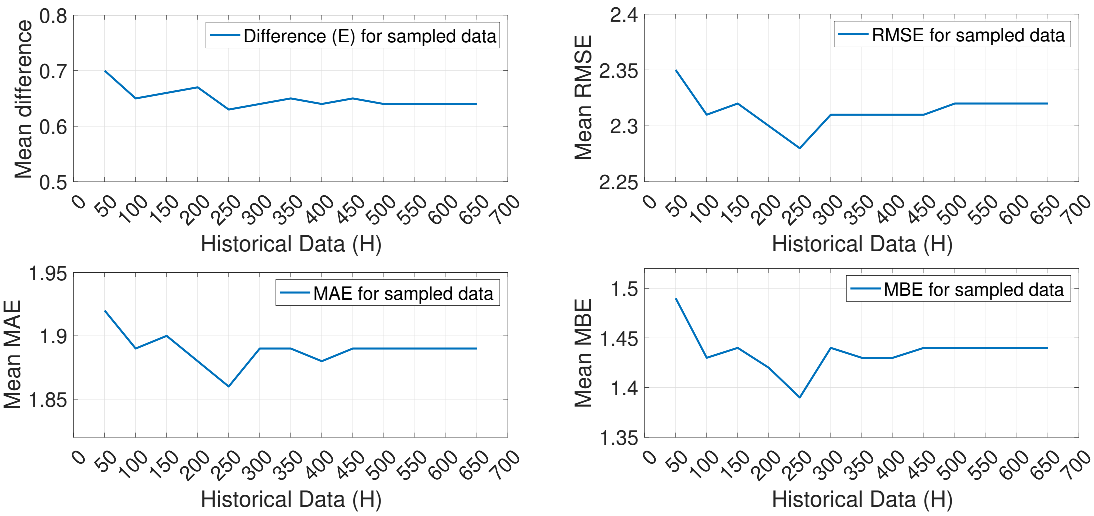

Figure C.3: Variations in Mean Errors with H for forecasting horizon of: 15 minutes

D | Input data for dispatcher verification

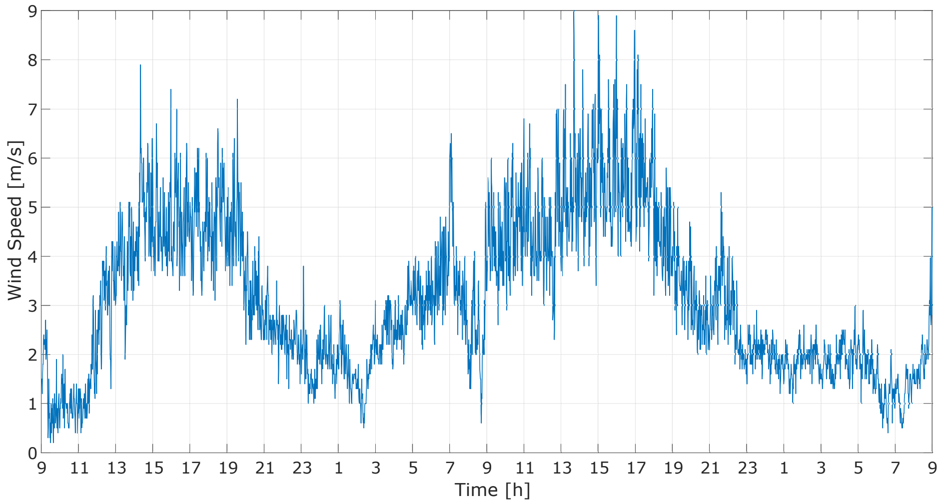

Figure D.1: Wind speed profile for 9 am 11.09.2018 - 9 am 13.09.2018

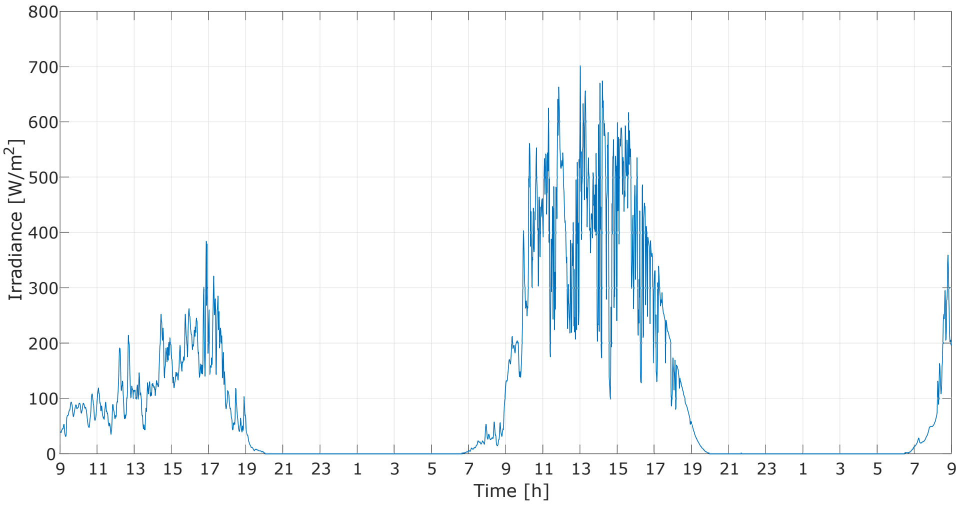

Figure D.2: Irradiance profile for 9 am 11.09.2018 - 9 am 13.09.2018

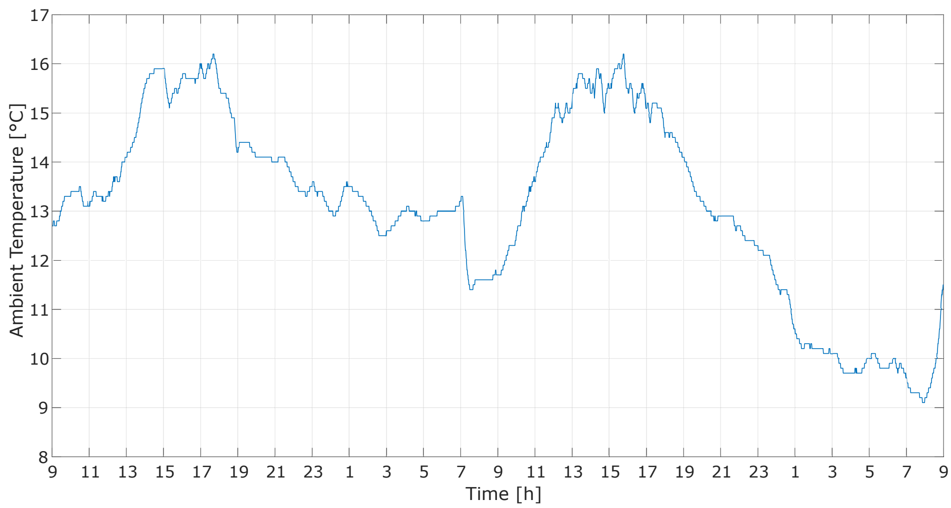

Figure D.3: Ambient temperature profile for 9 am 11.09.2018 - 9 am 13.09.2018

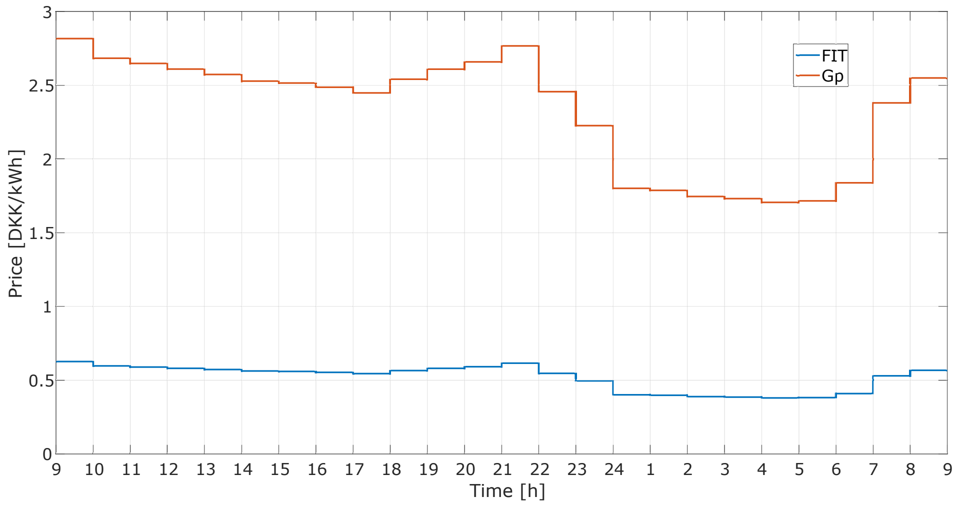

Figure D.4: Daily price profile for 9 am 11.09.2018 - 9 am 13.09.2018 [41]

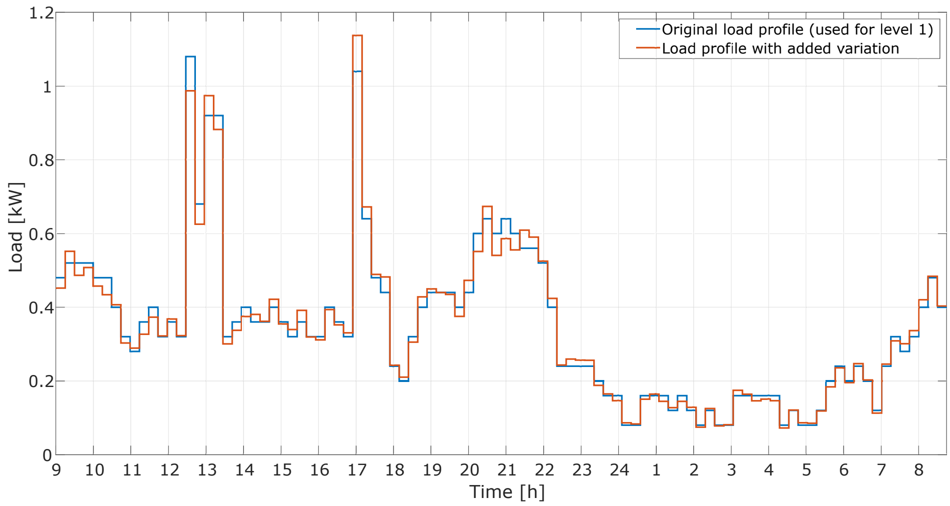

Figure D.5: Daily load profile for 9 am 11.09.2018 - 9 am 13.09.2018, and the one with added variation

Table D.1: Rest of the input data/parameters for the dispatcher study

Variable	**Value**	**Unit**
Rated battery energy	6.4/1	kWh/pu
Maximum SOC, SOC_{max}	5.76/0.9	kWh/pu
Minimum SOC, SOC_{min}	1.28/0.2	kWh/pu
Maximum battery power, P_{bat}^{max}	6.4	kW
Maximum grid current, I_{grid}^{max}	22	A
Initial state, SOC_{init}	3.2/0.5	kWh/pu
Final state, SOC_{end}	3.2/0.5	kWh/pu
EV type	Tesla Model 3	-
EV arrival time	19:00	hour
EV leaving time	07:00	hour
EV SOC state uppon arrival	0.7348	pu

D.1 Cost reduction

Table D.2: Dispatcher costs with SOC reference

δSOC^1	Δt^1 (min)	δSOC^2	Δt^2 (min)	Costs [DKK/day] Day ahead Degradation ↓	Day ahead Grid ↓	Day ahead Overall ↓	Actual Degradation ↓	Actual Grid ↓	Actual Overall ↓
0.1	15	0.001	5	1.22	13.21	14.44	1.52	16.68	18.20
			10	1.22	13.21	14.44	1.37	16.40	17.77
			15	1.22	13.21	14.44	1.30	16.15	17.45
		0.005	5	1.22	13.21	14.44	1.51	16.65	18.17
			10	1.22	13.21	14.44	1.35	16.20	17.54
			15	1.22	13.21	14.44	**1.27**	16.26	17.53
	30	0.001	5	1.22	12.36	13.58	1.58	16.60	18.18
			10	1.22	12.36	13.58	1.33	16.42	17.75
			15	1.22	12.36	13.58	1.35	16.42	17.77
		0.005	5	1.22	12.36	13.58	1.62	16.89	18.51
			10	1.22	12.36	13.58	1.41	17.07	18.48
			15	1.22	12.36	13.58	1.39	17.07	18.46
	60	0.001	5	1.53	7.29	8.82	1.68	16.37	18.05
			10	1.53	7.29	8.82	1.68	16.37	18.05
			15	1.53	7.29	8.82	1.64	16.46	18.10
		0.005	5	1.53	7.29	8.82	2.02	17.63	19.65
			10	1.53	7.29	8.82	1.74	17.29	19.03
			15	1.53	7.29	8.82	1.67	17.29	18.97
0.01	15	0.001	5	1.28	11.51	12.80	1.71	15.20	16.91
			10	1.28	11.51	12.80	1.44	**14.53**	**15.97**
			15	1.28	11.51	12.80	1.39	14.71	16.10
		0.005	5	1.28	11.51	12.80	2.01	17.49	19.50
			10	1.28	11.51	12.80	1.59	17.13	18.72
			15	1.28	11.51	12.80	1.50	17.27	18.77
	30	0.001	5	1.31	9.99	11.31	1.75	15.12	16.87
			10	1.31	9.99	11.31	1.51	14.79	16.29
			15	1.31	9.99	11.31	1.46	14.53	16.00
		0.005	5	1.31	9.99	11.31	2.13	17.43	19.56
			10	1.31	9.99	11.31	1.69	17.23	18.92
			15	1.31	9.99	11.31	1.54	17.22	18.76
	60	0.001	5	1.31	6.45	7.76	1.77	15.30	17.07
			10	1.31	6.45	7.76	1.50	14.95	16.44
			15	1.31	6.45	7.76	1.43	14.91	16.35
		0.005	5	1.31	6.45	7.76	2.10	17.27	19.37
			10	1.31	6.45	7.76	1.64	17.03	18.67
			15	1.31	6.45	7.76	1.54	17.13	18.67
Mean:							1.59	16.37	17.96

Table D.3: Cost savings for SOC reference cases

δSOC^1	Δt^1 (min)	δSOC^2	Δt^2 (min)	Savings [%] Day ahead Overall ↓	Day ahead Grid ↓	Day ahead Degradation ↓	Base Case Overall ↓	Base Case Grid ↓
0.1	15	0.001	5	-26.05	-26.23	-24.13	34.89	40.33
			10	-23.08	-24.08	-12.21	36.43	41.34
			15	-20.85	-22.24	-5.88	37.58	42.21
		0.005	5	-25.83	-26.03	-23.75	35.00	40.42
			10	-21.53	-22.58	-10.21	37.23	42.05
			15	-21.45	-23.09	-3.75	37.27	41.81
	30	0.001	5	-33.84	-34.30	-29.17	34.96	40.61
			10	-30.66	-32.83	-8.73	36.51	41.27
			15	-30.81	-32.84	-10.38	36.43	41.26
		0.005	5	-36.28	-36.66	-32.50	33.77	39.57
			10	-36.10	-38.15	-15.30	33.88	38.91
			15	-35.93	-38.12	-13.75	33.95	38.93
	60	0.001	5	-104.77	-124.61	-10.20	35.41	41.44
			10	-104.77	-124.61	-10.20	35.41	41.44
			15	-105.32	-125.84	-7.50	35.24	41.12
		0.005	5	-122.89	-141.96	-32.00	29.69	36.92
			10	-115.85	-137.32	-13.50	31.92	38.12
			15	-115.14	-137.31	-9.50	32.14	38.13
0.01	15	0.001	5	-32.14	-32.03	-33.10	39.50	45.61
			10	-24.78	-26.19	-12.22	42.87	48.02
			15	-25.79	-27.74	-8.33	42.40	47.38
		0.005	5	-52.35	-51.91	-56.35	30.24	37.43
			10	-46.30	-48.81	-23.81	33.01	38.70
			15	-46.67	-50.02	-16.67	32.85	38.21
	30	0.001	5	-49.22	-51.34	-33.14	39.63	45.90
			10	-44.12	-47.99	-14.77	41.70	47.10
			15	-41.49	-45.47	-11.28	42.76	48.00
		0.005	5	-73.00	-74.50	-61.63	30.01	37.62
			10	-67.38	-72.45	-28.88	32.29	38.35
			15	-65.89	-72.34	-16.86	32.89	38.39
	60	0.001	5	-119.89	-137.25	-34.77	38.91	45.26
			10	-111.81	-131.80	-13.72	41.16	46.51
			15	-110.53	-131.24	-8.95	41.52	46.64
		0.005	5	-149.50	-167.77	-59.88	30.69	38.21
			10	-140.45	-164.10	-24.42	33.20	39.06
			15	-140.50	-165.59	-17.44	33.19	38.71
Mean				-65.36	-73.54	-20.80	35.74	41.42

Table D.4: Average savings on all costs for SOC ref cases

Variable	**Value**
$\delta SOC^1 = 0.1$	34.87
$\delta SOC^1 = 0.01$	**36.60**
Δt^1= 15 minutes	**36.61**
Δt^1= 30 minutes	35.73
Δt^1= 60 minutes	34.87
$\delta SOC^2 = 0.001$	**38.52**
$\delta SOC^2 = 0.005$	32.96
Δt^2= 5 minutes	34.39
Δt^2= 10 minutes	36.30
Δt^2= 15 minutes	**36.52**

D.2 Grid Power following

Table D.5: Dispatcher costs with grid power reference

				Costs [DKK/day]						
				Day ahead			Actual			
δSOC^1	Δt^1 (min)	δSOC^2	Δt^2 (min)	Degradation ↓	Grid ↓	Overall ↓	Degradation ↓	Grid ↓	Overall ↓	SOC_{end} ↓
0.1	15	0.001	5	1.22	13.21	14.44	3.59	15.40	18.99	0.24
			10	1.22	13.21	14.44	2.87	16.37	19.24	0.24
			15	1.22	13.21	14.44	2.77	14.50	17.28	0.20
		0.005	5	1.22	13.21	14.44	3.13	14.98	18.12	0.20
			10	1.22	13.21	14.44	2.44	15.90	18.34	0.20
			15	1.22	13.21	14.44	2.24	14.60	16.84	0.21
	30	0.001	5	1.22	12.36	13.58	4.28	15.98	20.26	0.23
			10	1.22	12.36	13.58	3.41	16.54	19.95	0.23
			15	1.22	12.36	13.58	3.74	15.87	19.61	0.21
		0.005	5	1.22	12.36	13.58	3.95	16.62	20.58	0.22
			10	1.22	12.36	13.58	2.91	16.95	19.85	0.21
			15	1.22	12.36	13.58	3.41	16.60	20.01	0.20
	60	0.001	5	1.53	7.29	8.82	4.35	16.51	20.86	0.24
			10	1.53	7.29	8.82	4.03	18.50	22.53	0.24
			15	1.53	7.29	8.82	5.23	18.68	23.92	0.21
		0.005	5	1.53	7.29	8.82	3.59	18.24	21.83	0.34
			10	1.53	7.29	8.82	3.55	19.81	23.37	0.38
			15	1.53	7.29	8.82	4.44	20.19	24.63	0.34
0.01	15	0.001	5	1.28	11.51	12.80	3.54	14.33	17.88	0.22
			10	1.28	11.51	12.80	2.99	14.91	17.90	0.23
			15	1.28	11.51	12.80	2.88	**13.79**	**16.67**	0.20
		0.005	5	1.28	11.51	12.80	2.54	17.85	20.39	0.45
			10	1.28	11.51	12.80	2.30	18.28	20.58	**0.47**
			15	1.28	11.51	12.80	**1.80**	17.93	19.73	0.55
	30	0.001	5	1.31	9.99	11.31	4.52	14.90	19.41	0.30
			10	1.31	9.99	11.31	3.91	15.12	19.03	0.25
			15	1.31	9.99	11.31	4.29	14.91	19.19	0.30
		0.005	5	1.31	9.99	11.31	3.54	18.29	21.83	**0.47**
			10	1.31	9.99	11.31	3.23	17.92	21.15	0.37
			15	1.31	9.99	11.31	3.20	18.83	22.04	0.54
	60	0.001	5	1.31	6.45	7.76	4.98	17.97	22.95	0.37
			10	1.31	6.45	7.76	4.56	19.58	24.14	0.37
			15	1.31	6.45	7.76	5.81	19.66	25.47	0.37
		0.005	5	1.31	6.45	7.76	3.96	19.05	23.01	0.38
			10	1.31	6.45	7.76	3.69	19.98	23.68	0.38
			15	1.31	6.45	7.76	4.86	21.27	26.14	0.42
Mean:							3.63	17.13	20.76	

Table D.6: Grid power reference cases, savings

				Savings [%]					
	Compared to→			**Day ahead**				**Base Case**	
δSOC^1	Δt^1 (min)	δSOC^2	Δt^2 (min)	Overall ↓	Grid ↓	Degradation ↓	SOC end ↓	Overall ↓	Grid ↓
0.1	15	0.001	5	-31.54	-43.71	-193.13	-52.00	32.06	44.89
			10	-33.30	-45.64	-134.63	-52.80	31.15	41.42
			15	-19.68	-30.76	-126.75	-60.00	38.18	48.10
		0.005	5	-25.49	-37.11	-156.25	-60.00	35.18	46.40
			10	-27.03	-38.79	-99.38	-60.00	34.39	43.11
			15	-16.67	-27.47	-83.13	-58.20	39.74	47.75
	30	0.001	5	-49.17	-63.93	-249.50	-54.40	27.51	42.81
			10	-46.86	-61.40	-178.50	-54.60	28.63	40.82
			15	-44.38	-58.67	-205.88	-57.20	29.84	43.22
		0.005	5	-51.49	-66.49	-223.12	-56.40	26.38	40.52
			10	-46.16	-60.63	-137.50	-59.00	28.97	39.37
			15	-47.31	-61.89	-178.75	-59.20	28.41	40.61
	60	0.001	5	-136.57	-186.21	-184.40	-52.00	25.38	40.94
			10	-155.51	-209.13	-163.60	-51.20	19.40	33.82
			15	-171.28	-228.20	-242.10	-57.20	14.43	33.15
		0.005	5	-147.62	-199.58	-135.00	-32.20	21.89	34.75
			10	-165.04	-220.65	-132.50	-24.40	16.40	29.12
			15	-179.37	-237.99	-190.50	-32.00	11.88	27.77
0.01	15	0.001	5	-39.70	-55.29	-175.95	-56.00	36.04	48.72
			10	-39.86	-55.46	-132.62	-54.60	35.97	46.66
			15	-30.28	-44.81	-124.52	-60.00	40.35	50.67
		0.005	5	-59.35	-77.13	-97.62	-11.00	27.04	36.12
			10	-60.84	-78.79	-79.17	-6.44	26.36	34.59
			15	-54.17	-71.37	-39.88	10.76	29.41	35.84
	30	0.001	5	-71.71	-94.31	-243.37	-40.88	30.54	46.69
			10	-68.28	-90.43	-196.98	-49.24	31.92	45.90
			15	-69.77	-92.11	-225.93	-40.48	31.32	46.66
		0.005	5	-93.11	-118.52	-169.19	-5.50	21.88	34.55
			10	-87.06	-111.68	-145.35	-26.66	24.33	35.87
			15	-94.91	-120.56	-143.60	7.28	21.15	32.61
	60	0.001	5	-195.59	-255.86	-278.37	-25.78	17.88	35.69
			10	-210.96	-274.36	-247.09	-26.00	13.62	29.95
			15	-228.07	-294.96	-341.98	-26.60	8.86	29.66
		0.005	5	-196.39	-256.83	-201.16	-24.30	17.66	31.83
			10	-204.94	-267.12	-180.81	-24.32	15.29	28.50
			15	-236.63	-305.27	-269.77	-16.28	6.48	23.88
Mean				-95.45	-126.20	-175.22	-39.13	25.72	38.69

Table D.7: Average savings on all costs for grid power reference cases

Variable	**Value**
$\delta SOC^1 = 0.1$	**27.21**
$\delta SOC^1 = 0.01$	24.23
Δt^1= 15 minutes	**33.82**
Δt^1= 30 minutes	27.57
Δt^1= 60 minutes	15.76
$\delta SOC^2 = 0.001$	**27.39**
$\delta SOC^2 = 0.005$	24.05
Δt^2= 5 minutes	**26.62**
Δt^2= 10 minutes	25.53
Δt^2= 15 minutes	25.01