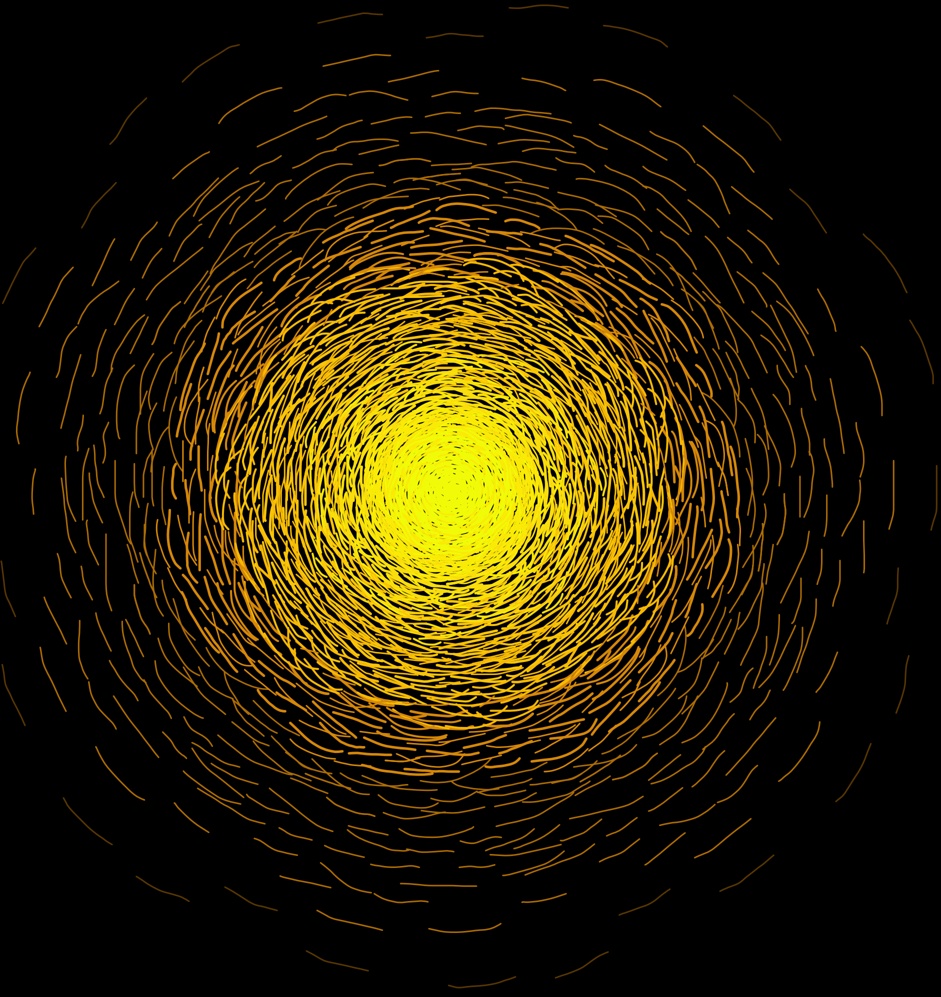
Local Energy Trading for Microgrids

Modeling Human Behavior, Uncertainty and Grid Constraints



Jens Hönen

Local Energy Trading for Microgrids

Modeling Human Behavior, Uncertainty and Grid Constraints

Dissertation

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Abstract

Electricity is one of the major drivers of today's society and a crucial element of the rapid development of humankind over the last 150 years. However, in its current form, it also significantly contributes to the (man-made) global warming, a potential threat to the current and future society. One way to reduce the impact on global warming is to change the electricity production. This change requires a switch from fossil fuels, such as oil, coal, or natural gas to more renewable and sustainable energy sources, such as wind, hydro, solar, or geothermal energy and it is a core part of the so-called energy transition. Other aspects of the energy transition encompass large changes in heating systems or mobility, where fossil fuels in the form of oil or gas are replaced by electricity.

The mentioned changes have a significant impact on the current electricity system, which was developed over the last 100 years. Along with the switch from fossil fuels to renewable sources comes a whole change in the way electricity is produced. Instead of controlling a few, large central power plants, the future electricity system will be powered by a myriad of decentralized, small-scale electricity producers, which usually do not offer the same range of control as known in traditional power plants. In addition, the overall electricity demand sharply increases due to the electrification of mobility and heating. The current electricity grid was not built to serve all these loads and places of production and generation. To avoid huge financial investments into fixing and strengthening the current grid, an intelligent (active) management of the electricity production and consumption is, therefore, crucial for a stable future electricity distribution.

In research, there are various approaches to such active steering of the electricity production and consumption, and they are commonly classified as energy management systems (EMS) or local energy trading approaches. These approaches may be based on a variety of different mathematical, game-theoretic, or economic theories and concepts. Furthermore, the intended application scenarios of such EMSs differ and can range from controlling the devices of a single household to managing the demand and supply of a whole neighborhood or city. Along with the more decentralized electricity generation in the form of wind power farms and photovoltaic (PV) systems, future EMSs will often also work on a much smaller scale compared to the traditional and global approach reflected in the unit commitment problem. The objective of these future EMSs may differ depending on the application, but commonly researched goals are the minimization of electricity costs, the maximization of self-consumption of locally produced PV generation, or the minimization of the impact on the electricity grid.

At the core of this thesis, we focus on three different aspects of EMSs, which enable households to participate in (local) electricity markets. The main contributions of this thesis are:

» We consider the impact of human behavior on the outcome of a local electricity market (LEM). With the increasing local production of PV power in residential households, these households are able to directly participate in LEMs. This participation increases society's acceptance of the energy transition and allows households to profit from this change. However, from the perspective of the LEM, the direct participation of households also brings new challenges and open questions. One such question is how the human behavior aspect of household participation may affect the outcome of the LEM. To answer this question, we aim to model and integrate human behavior and preferences into a home energy management system (HEMS), which bridges the gap between end-participants and the LEM. To model this aspect, we first compare various behavioral models from social science and psychology and then translate one such behavioral model into a (multi-objective) optimization model, which serves as the core of the HEMS. Thereby, households can input their personal preferences and motives into their HEMS, which then creates and submits a tailor-made bidcurve. We analyze the impact of human behavior on a LEM on two levels. The first analysis focuses on the impact of human behavior on the bidcurve of an individual household. In a second step, we then analyze the impact of different parameter choices on the outcome of the LEM.

» A second aspect of this thesis concerns the increased uncertainty in the future energy system. Due to the change in electricity production, additional uncertainty in the form of intermittent PV and wind generation has to be considered. However, electricity generation is not the only additional source of uncertainty. The concrete arrival and departure of electric vehicles (EV) is a further source of uncertainty, as is the demand of EVs or heat pumps (HP). Dealing with uncertainty on an individual household level requires detailed forecasts (in particular) for individual demand profiles, which is known to be very difficult to achieve. On the other hand, forecasts for aggregated profiles, such as the aggregated household load of a neighborhood, are already well-established. Therefore, we tackle the issue of dealing with uncertainty from the perspective of a microgrid, which consists of a set of households, such as a neighborhood. The goal of the microgrid is to jointly act as one entity at the classical day-ahead and intraday electricity markets, subject to a wide range of uncertainties, ranging from electricity prices to household loads and PV generation. We use ideas and techniques from robust optimization to deal with the uncertainty, as the focus on feasibility and the often conservative solutions fit well with the rules and requirements of the current (and future) electricity system. The main contribution is an in-depth analysis of an approach combining a rolling horizon framework with (static) robust optimization. We first analyze the impact of the various uncertainty sources on the results of the approach, and thereby highlight the importance of the times at which decisions are made. Based on this insight, we further develop a classical rolling horizon approach by allowing a more flexible scheduling of the individual rolling horizon iterations. The accompanying scheduling algorithm is based on expected improvements in (PV) forecasts, and its combination with the rolling horizon idea already leads to substantial improvements in the objective value. In a second step, we identify weaknesses of the proposed tailor-made scheduling scheme and propose an online scheduling tool, which is better able to react to improved forecasts and realized uncertainties. We analyze and show the advantages of the online rolling horizon scheme and again observe improvements in the objective value and the local PV usage over the previous two rolling horizon schemes.

» A third aspect focuses on grid constraints in energy trading and management. We combine this focus with the research question of how the day-ahead (and intraday) solutions, which are usually built up for 15-minute time slots, can be realized within such a single time slot. Due to the finer time granularity, peaks and differences in demand and production do not cancel out each other, leading to potentially larger fluctuations in the electricity grid than expected at the day-ahead operation stage. Therefore, the focus on grid constraints is of high importance in real-time control to ensure a stable electricity distribution. Based on these observations, we propose a real-time control and balancing algorithm for a set of microgrids, which uses the day-ahead solution to guide the real-time control decisions. We thereby ensure that the day-ahead decisions are implemented as planned, and also allow for the design of an online algorithm, which makes decisions without any information on future time slots. The approach can be described as a three-step framework, in which the first step consists of ensuring the feasibility of devices within the microgrids. The second step focuses on the grid constraints using the DC power flow formulation due to the running time requirements of the real-time approach. The last step is to propagate the solution into the individual microgrids, where the allocated power needs to be distributed among the devices and households. Within a case study, we show that the proposed real-time control approach works as intended and leads to results comparable to an optimal offline algorithm. In addition, we identify some interesting, often ignored connections between day-ahead operations and their real-time realization.

Samenvatting

Elektriciteit is een van de belangrijkste motoren van de huidige samenleving en een cruciaal element van de snelle ontwikkeling van de mensheid in de afgelopen 150 jaar. In zijn huidige vorm draagt het echter ook aanzienlijk bij aan de (door de mens veroorzaakte) opwarming van de aarde, een potentiële bedreiging voor de huidige en toekomstige samenleving. Eén manier om de impact op de opwarming van de aarde te verminderen is door de elektriciteitsproductie te veranderen. Deze verandering vereist een omschakeling van fossiele brandstoffen, zoals olie, kolen of aardgas, naar meer hernieuwbare en duurzame energiebronnen, zoals wind-, zonne- en geothermische energie, of waterkracht en is een kernonderdeel van de zogenaamde energietransitie. Daarnaast omvat de energietransitie grote veranderingen voor verwarmingssystemen en mobiliteit, waarbij fossiele brandstoffen in de vorm van olie of gas worden vervangen door elektriciteit.

De genoemde veranderingen hebben een grote impact op het huidige elektriciteitssysteem, dat in de afgelopen 100 jaar is ontwikkeld. Samen met de omschakeling van fossiele brandstoffen naar hernieuwbare bronnen komt er een hele verandering in de manier waarop elektriciteit wordt geproduceerd. In plaats van de controle over een paar grote centrale elektriciteitscentrales, zal het toekomstige elektriciteitssysteem worden aangedreven door een groot aantal gedecentraliseerde, kleinschalige elektriciteitsproducenten, die meestal niet dezelfde mate van controle bieden als de traditionele elektriciteitscentrales. Bovendien neemt de totale vraag naar elektriciteit sterk toe door de elektrificatie van mobiliteit en verwarming. Het huidige elektriciteitsnet is niet gebouwd om al deze belastingen en plaatsen van productie en opwekking te bedienen. Om enorme financiële investeringen in het herstellen en versterken van het huidige net te vermijden, is een intelligent (actief) beheer van de elektriciteitsproductie en -consumptie daarom cruciaal voor een stabiele elektriciteitsdistributie in de toekomst.

In de onderzoekswereld zijn er verschillende benaderingen voor een dergelijke actieve sturing van de elektriciteitsproductie en -consumptie. Die worden vaak geclassificeerd als energiemanagementsystemen (EMS) of lokale energiehandelsbenaderingen. Deze benaderingen kunnen gebaseerd zijn op verschillende wiskundige, speltheoretische of economische theorieën en concepten. Bovendien verschillen de beoogde toepassingsscenario's van dergelijke EMSs en kunnen ze variëren van het besturen van de apparaten van een enkel huishouden tot het beheren van de vraag en het aanbod van een hele buurt of stad. Samen met de meer gedecentraliseerde elektriciteitsopwekking in de vorm van windmolenparken en fotovoltaïsche (PV)-systemen, zullen toekomstige systemen vaak ook op

een veel kleinere schaal werken in vergelijking met de traditionele en globale aanpak die tot uiting komt in het unit commitment probleem. Het doel van deze toekomstige systemen kan verschillen afhankelijk van de toepassing, maar de meest onderzochte doelen zijn het minimaliseren van de elektriciteitskosten, het maximaliseren van het eigen verbruik van lokaal geproduceerde PV-generatie of het minimaliseren van de impact op het elektriciteitsnet.

In deze dissertatie richten we ons op drie verschillende aspecten van EMSs, die huishoudens in staat stellen om deel te nemen aan (lokale) elektriciteitsmarkten (LEM). De belangrijkste bijdragen van dit proefschrift zijn:

» We houden rekening met de impact van menselijk gedrag op het resultaat van een LEM. Met de toenemende lokale productie van zonne-energie in huishoudens, kunnen deze huishoudens direct deelnemen aan de energietransitie. Deze participatie vergroot de maatschappelijke acceptatie van de energietransitie en stelt huishoudens in staat om te profiteren van deze verandering. Vanuit het perspectief van de LEM brengt de directe participatie van huishoudens echter ook nieuwe uitdagingen en open vragen met zich mee. Eén zo'n vraag is hoe het menselijke gedragsaspect van de deelname van huishoudens het resultaat van het project kan beïnvloeden. Om deze vraag te beantwoorden, willen we menselijk gedrag en voorkeuren modelleren en integreren in een huishoudelijk-energiemanagementsysteem (HEMS) dat de kloof tussen einddeelnemers en het systeem overbrugt. Om dit aspect te modelleren, vergelijken we eerst verschillende gedragsmodellen uit de sociale wetenschappen en de psychologie en vertalen we vervolgens één zo'n gedragsmodel in een (multi-objectief) optimalisatiemodel, dat dient als de kern van het HEMS. Daarbij kunnen huishoudens hun persoonlijke voorkeuren en motieven invoeren in hun HEMS, dat vervolgens een op maat gemaakte biedcurve creëert en voorlegt. We analyseren de impact van menselijk gedrag op een LEM op twee niveaus. De eerste analyse richt zich op de impact van menselijk gedrag op de biedcurve van een individueel huishouden. In een tweede stap analyseren we de impact van verschillende parameterkeuzes op de uitkomst van de biedcurve.

» Een tweede aspect van dit proefschrift betreft de toegenomen onzekerheid in het toekomstige energiesysteem. Door de verandering in de elektriciteitsproductie moet er rekening worden gehouden met extra onzekerheid in de vorm van onberekenbare PV- en windopwekking. De opwekking van elektriciteit is echter niet de enige extra bron van onzekerheid. De precieze aankomst en het vertrek van elektrische voertuigen is een andere bron van onzekerheid, net als de vraag naar elektrische voertuigen (EV) of warmtepompen. Om met onzekerheid op het niveau van individuele huishoudens om te gaan, zijn (vooral) gedetailleerde voorspellingen voor individuele profielen nodig, waarvan bekend is dat ze zeer moeilijk te verwezenlijken zijn. Aan de andere kant zijn voorspellingen voor geaggregeerde profielen, zoals de geaggregeerde huishoudbelasting van een buurt, al goed ingeburgerd. Daarom pakken we het omgaan met onzekerheid aan vanuit het perspectief van een microgrid, dat bestaat uit een verzameling huishoudens, zoals een buurt. Het doel van het microgrid is om gezamenlijk als één entiteit op te treden op de klassieke day-ahead en intraday elektriciteitsmarkten, die onderhevig zijn aan een groot aantal onzekerheden, variërend van elektriciteitsprijzen tot huishoudelijke belastingen en PV-opwekking. We gebruiken ideeën en technieken van robuuste optimalisatie om met de onzekerheid om te gaan, omdat de focus op haalbaarheid en de vaak conservatieve oplossingen goed passen bij de regels en vereisten van het huidige (en toekomstige) elektriciteitssysteem. De belangrijkste bijdrage is een diepgaande analyse van een aanpak die een rolling horizon-methode combineert met (statische) robuuste optimalisatie. We analyseren eerst de invloed van de verschillende bronnen van onzekerheid op de resultaten van de aanpak en benadrukken daarbij het belang van de tijdstippen waarop beslissingen worden genomen. Op basis van dit inzicht ontwikkelen we een klassieke rolling horizon-benadering verder door een flexibelere planning van de individuele rolling horizon iteraties toe te staan. Het bijbehorende planningsalgoritme is gebaseerd op verwachte verbeteringen in (prognoses van) de voorspellingen, en de combinatie met het rolling horizon-idee leidt al tot aanzienlijke verbeteringen in de doelfunctiewaarde. In een tweede stap identificeren we de zwakke punten van het voorgestelde op maat gemaakte planningsschema en stellen we een online planningshulpmiddel voor dat beter in staat is om te reageren op verbeterde voorspellingen en gerealiseerde onzekerheden. We analyseren en tonen de voordelen van het online planningsschema met een rolling horizon en zien opnieuw verbeteringen in de doelfunctiewaarde en het gebruik van de lokale PV ten opzichte van de vorige twee planningsschema's met een rolling horizon.

» Een derde aspect richt zich op netbeperkingen bij de handel in en het beheer van energie. We combineren deze focus met de onderzoeksvraag hoe de day-ahead (en intraday) oplossingen, die normaal gesproken zijn opgebouwd voor tijdsloten van 15 minuten, kunnen worden gerealiseerd binnen zo'n enkel tijdslot. Door de fijnere tijdsschaal heffen pieken en verschillen in consumptie en productie elkaar niet op, wat leidt tot potentieel grotere fluctuaties in het elektriciteitsnet dan verwacht in de dayaheadoperatiefase. Daarom is de focus op netbeperkingen van groot belang bij realtime regeling om een stabiele elektriciteitsdistributie te garanderen. Op basis van deze observaties stellen we een realtime regel- en balanceringsalgoritme voor voor een reeks microgrids, dat de day-ahead oplossing gebruikt om de realtime regelbeslissingen te sturen. Zo zorgen we ervoor dat de day-ahead beslissingen worden uitgevoerd zoals gepland, en maken we het ook mogelijk om een online algoritme te ontwerpen dat beslissingen neemt zonder enige informatie over toekomstige tijdsloten.

De aanpak kan worden beschreven als een methode met drie stappen, waarbij de eerste stap bestaat uit het waarborgen van de haalbaarheid van apparaten binnen de microgrids. De tweede stap richt zich op de netbeperkingen met behulp van de DC-power flow vanwege de looptijdvereisten van de realtime benadering. De laatste stap is het propageren van de oplossing naar de individuele microgrids, waar het toegewezen vermogen verdeeld moet worden over de apparaten en huishoudens. In een casestudy laten we zien dat de voorgestelde realtime regelaanpak werkt zoals bedoeld en leidt tot resultaten die vergelijkbaar zijn met een optimaal offline algoritme. Daarnaast identificeren we een aantal interessante, vaak genegeerde verbanden tussen day-ahead operaties en de realtime realisatie ervan.

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Writing these words, my Ph.D. journey - and a significant chapter in my life - is slowly coming to an end. The last nearly five years have been characterized by many ups and downs. While at some points, it seemed as if I was not moving forward at all, at others, time flew by without me realizing it. One thing, however, that remained constant throughout all the journey, has been the never ending support of people around me. Without you, I would certainly not have been able to finish this thesis.

First of all, I would like to thank my two promotors, Johann and Bert. You both gave me all the freedom I could have imagined to identify, explore and research what I found interesting within the broad area of the energy transition. This freedom has led me towards the topics of this thesis, even though it was sometimes a slow and challenging process for me to find the (right) way. However, whenever I asked for it, you provided the necessary guidance for me to take the next step.

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by Sjoerd and myself. I would also like to thank all remaining AGILE project members for their collaboration throughout the last years.

Within the UT, I was closest to the energy group. I have watched how the group grew significantly during the last few years - from the start, when basically the whole energy group would fit into the energy shed, up to today, where even several rooms are not sufficient for all of us. I would like to thank all of you for the warm welcome, both, when I started my journey, as well as when I (finally) joined the UT again after quite some time of home office. I have always enjoyed the atmosphere in the energy group, which encouraged to engage in discussions and to seek your advice when I was having questions or encountered difficulties. Hopefully, I could also contribute to some of your discussions and questions. The coffee breaks and lunch walks were a welcome opportunity to get to know you beyond your work, and I have always enjoyed our conversations. Thank you all for the great time!

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Finally, I would like to thank my mother and my sister. Without your support, I would certainly not have been able to finish my Ph.D. journey. You have always believed in me, even when I did not. I could always share my experiences, thoughts and plans with you, and received valuable advice from you. Thank you for always having my back!

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Enschede, March 2024

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1

Introduction

Abstract – *This chapter describes the scope of this thesis. Firstly, it outlines the ongoing challenges of the energy transition, which explains the need for energy management and control approaches to ensure a stable electricity distribution in the future. Based on this, the main research questions considered in this thesis are introduced and an overview of the contributions and the structure of the thesis is provided.*

1.1 Energy Transition

Climate change is one of the most prominent and severe long-term problems humankind has to face [112]. In particular, during the last years, we have started to face the first consequences, and extreme weather events, such as droughts, heatwaves, or floodings are increasing in intensity and frequency [49, 237]. To limit the ongoing climate change and restrict the temperature increase to well below 2 ° C by 2100, nearly all countries have signed and ratified the Paris Agreement [77, 216] with the aim to reduce greenhouse gas emissions.

One important approach in reducing these emissions is the *energy transition*, which represents a fundamental change of the current energy system and consists of two main pillars:

» *Decarbonization of electricity generation*: The decarbonization of the electricity generation focuses on the shift from using fossil fuels such as coal, gas, or oil to more renewable and sustainable energy sources. Within the last decades, much progress has been made in the development of technologies that are able to generate electricity from renewable energy sources (RES), such as geothermal energy, solar irradiation, wind, or water. In addition to the lower emission of greenhouse gas compared to coal or gas power plants, the underlying energy sources are also not scarce or limited in their worldwide deposits. Therefore, RES may build the foundation of electricity generation for the next generations.

» *Electrification of fossil-based processes*: Besides the decarbonization of the electricity generation, the electricity generated from RES can also be used to replace other fossil-based processes, such as residential heating or mobility. Instead of burning oil or gas to move cars or heat houses, recent developments in battery and heat pump (HP) technology enable the usage of electricity for these tasks.

  The electrification of energy supply also applies to processes beyond residential tasks. In the industry, some tasks, such as e.g., steel production, require large amounts of high-temperature heat for its processes. One opportunity is to replace the current fossil fuels such as natural gas or coal with green hydrogen produced using electricity from RES [28].

These changes induce new problems and challenges in the electricity system, that need to be tackled to ensure a stable electricity distribution and supply in the future. Among the problems and challenges are:

» *Inability to directly control the generation of RES*: Compared to conventional fossil fuel-based power plants, in which the electricity generation can be fully controlled, the production of many RES often depends on weather conditions or other external factors, which are beyond human control. While a curtailment of the electricity generation is possible, an increase of the production is not. As the safe operation of the electricity system depends on the balance between demand and supply, the paradigm of supply follows demand has been applied in the past. With the gradual shift towards non-controllable electricity generation, this paradigm no longer holds. Instead, in future electricity systems, demand needs to follow supply. This in turn requires the control and management of a large set of often small devices, such as e.g., batteries, electric vehicles (EV), or HPs to steer the demand accordingly.

» *Difficulty to accurately predict the generation of RES*: In addition to the difficulty of matching demand and supply due to a lack of control, the dependency of RES generation on external factors, such as the weather also leads to problems and challenges with the predictability and accuracy of forecasts. Due to rather similar weather in small areas, such as a city or town, the production of e.g., wind power farms or photovoltaic (PV) systems within these areas is highly correlated, emphasizing the need for good predictions and forecasts.

» *Increase in peaks in production and consumption*: Due to the electrification in many areas of society and industry, peak power in production and consumption will drastically increase. These peaks are of particular concern w.r.t. the underlying electricity grid and its components such as cables and transformers, which are not properly sized for such increased loads. A seemingly simple solution to this problem is to reinforce and strengthen the grid with these new peaks in mind. However, this would incur massive investments, which are only used and necessary during the small fraction of the year, in which these peaks may occur.

All of the challenges and problems we elaborated on above call for some form of control over supply and demand to ensure a stable electricity distribution in the future. In recent years, quite some research has been done on such energy control and management approaches, whereof one strand of research focuses on the concept of (local) electricity markets (LEM) [35]. The main idea behind LEMs is to allow households or other small entities to directly participate in electricity trading with neighbors, suppliers, or other participants. Within this thesis, we focus on such electricity trades and propose, test, and analyze various approaches and algorithms, tackling different aspects of local electricity trading and markets.

1.2 Research Question and Contributions

This thesis aims to contribute to the ongoing development of approaches and algorithms in the vast area of local energy management and trading. The central research questions of this thesis are therefore:

> *RQ1: Given the current state of local energy trading approaches, what aspects are missing or neglected?*

and

> *RQ2: How can these aspects be addressed?*

We consider the first research question in Chapter 3, where we provide a review and classification scheme of the current state of the literature on local energy trading approaches. We identify three distinct research directions, each applying different concepts and techniques for local energy trading. In addition to these three directions, we identify several characteristics or aspects of local energy trading, which mostly are neglected in the literature. Based on these insights, we split the second part of the research question into the following three subquestions:

> *RQ2.1: How can we model human behavior and evaluate its impact on the outcome of local energy trading?*

To address this first aspect, namely human behavior and its impact on local energy trading approaches, we consider the setting of a local electricity market, in which individual households can participate by submitting their own bids. To model human behavior, we first analyze and compare various behavioral models from social science. We then translate one such behavioral model into a mathematical optimization problem, which may serve as the core of a home energy management system (HEMS), bridging the gap between households and the market. The input parameters of the model represent various aspects of human behavior, while the output corresponds to a bidcurve, which is used as the input for the local electricity market. To gain insights into the impact of human behavior on local energy trading, we analyze both, the individual bidcurve of a single household as well as the outcome of a set of households participating in the local electricity market. Within the discussion, we can confirm our gained insights with the claims and characteristics of the original behavioral model and derive implications for future market design.

> *RQ2.2: How can we deal with uncertainty in data and forecasts?*

We address the aspect of uncertainty in local energy trading approaches in the context of a joint day-ahead energy operation problem for a microgrid with access to multiple electricity markets. Due to the time between decision-making and the actual realization of uncertain data, uncertainty plays an important role in this market setting. We propose two main approaches, both using different techniques from robust optimization to ensure feasibility in the presence of uncertain demand, supply, and electricity prices. We evaluate and analyze both approaches in a case study, and use the gained insights to further develop one of the two approaches beyond its base version. Hereby, the key insight lies within the influence of the individual uncertainty sources on the resulting solutions and objective values. In particular taking into account time-dependent uncertainty, as observed in the forecast of PV generation, contributes to improvements in the objective value. Therefore, the development of the second approach focuses on the timing aspect of decision-making and we can show that substantial improvements over the base version can be achieved.

> *RQ2.3: How can we ensure that local energy trading approaches are grid-feasible?*

For this aspect, namely grid constraints, we consider the real-time implementation of day-ahead market solutions, as addressed in the previous subquestion, for a set of microgrids. The planned energy exchange with the electricity markets in the presence of fluctuating demand and supply is realized by letting microgrids trade with each other. These additional trades may, however, impact the medium-voltage (MV) distribution grid connecting the microgrids with each other and with the market. To ensure that the grid constraints on this level are not violated, we propose a three-step framework, which implements the day-ahead solutions of the microgrids in real-time, while respecting the grid constraints of the connecting MV grid. The modular nature of the framework allows an easy adaptation to different settings and scenarios, such as the implementation in a neighborhood. To validate the approach w.r.t. the objective as well as the computational time, we test the framework in a case study, and compare it to an optimal offline solution approach, which serves as one part of the benchmark.

1.3 Outline

The remainder of this thesis is structured as follows:

Chapter 2 first introduces the general concept of a microgrid, which is widely used in research on energy management and trading approaches. We also provide an introduction to various solution techniques for energy management problems, which can be found in the literature. Chapter 3 then provides an overview and classification scheme of the current state of the literature on local energy trading and gives three aspects or characteristics, which up to now have been neglected in large parts of literature. Chapter 4 tackles the first aspect, namely the impact of human behavior on local energy markets. We use a well-established behavioral model from the social sciences and translate it into a mathematical optimization problem, whose output is a bidding curve for a local electricity market. We investigate and analyze the impact of household parameters reflecting human behavior on the local electricity market. Chapter 5 concerns the second neglected aspect, namely uncertainty in data. We focus on the application of robust optimization to deal with the uncertainty in energy systems and propose and compare two different approaches. Chapter 6 introduces the third aspect, namely grid constraints, into local energy trading and management. We focus on a real-time control and balancing problem between microgrids in the MV grid, and show that the proposed three-step approach can be solved efficiently while respecting grid constraints. Chapter 7 summarizes the main contributions of this thesis and provides an outlook to interesting research directions and questions.

2

Modeling of microgrids

Abstract – *In this chapter, the central concept of a microgrid, which is a key component in the current research on energy management approaches as well as in the remainder of this thesis, is introduced. Different participants, devices, and components of a microgrid are presented, followed by a mathematical formulation for the various devices and physical constraints. Finally, an overview of common mathematical and game-theoretic solution techniques, which are used in the literature to solve optimization problems related to microgrid settings, is provided.*

2.1 Introduction

In the energy transition, one very commonly used concept is that of a microgrid, which is a set of households connected via the electricity grid. One example of such a microgrid may be a neighborhood. The main idea behind the microgrid is that a set of households can (jointly) manage their energy consumption and production. All throughout this thesis, we make use of this concept in various forms. To avoid repetitions, we use this chapter to formally introduce the concept, its components, and other aspects, such as solution techniques, which may be important later on in the thesis.

This chapter is structured as follows: In Section 2.2, we provide a general introduction and definition of the considered entities, components, and other aspects of a microgrid. We then proceed with a mathematical formulation of the microgrid in Section 2.3. In Section 2.4, we shortly discuss and provide an overview of various solution techniques, which have been used extensively throughout literature.

This chapter is mainly based on parts of [JH:1] and [JH:3].

2.2 Participants and Components

In the literature, the concept of a microgrid is not clearly defined and various versions and extensions, with often minor differences, exist [140, 197]. Therefore, within this section, we provide a general definition of a residential microgrid, as used within this thesis. We start with an overview of the key participants of a microgrid, namely the *households*, including their devices and loads. We then proceed with the *microgrid operator* and an overview of *electricity markets* and other ways how to trade electricity within and beyond the microgrid. We conclude this section with a short overview of the (current) electricity grid.

2.2.1 Household

The core of each residential microgrid is the set of participating households. Within this work, we assume that these are residential households. Each household may be equipped with various devices, which either offer flexibility or have a large impact on the system, and are therefore key components in any future energy management system (EMS). Within the following, we assume that each household may be equipped with a variety of devices, which may be controlled by a HEMS.

Devices

» *Photovoltaic system*: Within the last few years, (residential) PV systems have become increasingly popular [44]. These systems can transform solar irradiance into electric power. Hence, PV production heavily depends on the weather conditions, and the only control possible is curtailment.

» *Battery*: Batteries serve as buffers within the electricity system. They can store electricity over time, that is they can be charged at some point and discharged at a later point in time. Batteries are limited by maximum power limits on charging and discharging, as well as a capacity limit. In addition, some energy is lost during charging and discharging, which is modeled via charging and discharging efficiencies. Various battery technologies exist, which may differ in their efficiencies and power limits.

» *Electric vehicle*: Electric vehicles (EV) are one form of removing fossil fuels from mobility and transport. At its core, an EV is a battery with arrival and departure times and a demand, which is subtracted. The demand depends on the driving distance and other aspects, such as vehicle heating or cooling.

» *Heat pump*: HPs electrify another aspect of everyday life, namely (residential) heating and cooling. A HP transforms electricity into thermal energy, which can be used to heat or cool the house. The efficiency of the transformation varies between models, but in general, it depends on the difference between the outside temperature and the required temperature for heating. The heat demand of a house also depends on various characteristics of the house, such as the insulation, the difference between the current and the target temperature, and other external influences, such as the heating due to solar irradiance.

In some parts of literature, households may be referred to as *prosumers*. This term underlines the ability of a household to not only consume electricity but also to produce or feed electricity into the grid by means of PV systems, batteries and EVs. Within the remainder of this thesis, we may use both terms.

Loads

Apart from the controllable loads of the above-presented devices, the household also consumes electricity for cooking, lighting, cooling or washing. Some of these activities are not controllable by the HEMS, while others may pose a certain limited range of flexibility to the energy management or trading approach. In the following, we shortly present examples of such loads:

» *Inflexible load*: Some part of the household load is inflexible, i.e. it cannot be changed. Examples of such load sources are lighting, cooking, or TV. Other electricity sources, such as a dishwasher or the washing machine, which are in principle able to shift their load in time, by starting earlier or later, are within the context of this work also considered to be inflexible.

» *Time-shiftable load*: In some parts of the literature, time-shiftable devices, such as a dishwasher or the washing machine, are explicitly considered. Such devices have a fixed demand profile once they are started, however the starting time offers flexibility.

» *Curtailable load*: Some approaches in the literature assume that a certain fraction of the household load can be curtailed and thereby not served, if necessary.

See [108] for a more detailed overview of the different types of loads and devices.

Home Energy Management Systems

Many of the above-introduced devices need to be steered and controlled. Instead of doing this work manually and setting the charging and discharging levels of batteries and EVs or HPs by hand, we assume that a HEMS does this task. It manages and controls all the (steerable) devices within a household and is also responsible for the (automated) communication with the central microgrid operator.

2.2.2 Microgrid Operator

Apart from the households, we also consider a microgrid operator (MGO), which mainly serves as an aggregator within the microgrid [102]. The MGO coordinates the communication, computation, and interactions between the households and possibly external parties. Within this thesis, we mainly consider centralized solution approaches, which we assume to be run by the MGO. It therefore needs to collect the necessary data of the individual households, process these data, and solve the optimization model. It then communicates the individual household solutions to the households, where the HEMSs can then realize the planned solution.

In addition, the MGO acts as the representative of the microgrid if interacting with external parties or entities, such as the electricity markets. Hence, the MGO, based on a jointly-made solution, buys and sells electricity in the name of the whole microgrid at the various electricity markets. In some settings, households may not be equipped with a battery, but a central, *communal battery* is shared among all households of the microgrid. The MGO then directly controls and manages such communal devices.

2.2.3 Energy Trading and Markets

Electricity markets are the most important external parties that interact with the MGO. In the current electricity system, there exist multiple such markets, where electricity is traded. These markets mainly differ in the time scale between closing the market and the delivery of the traded electricity. This time scale ranges from up to four years to a month for forward energy markets, over a day up to an hour ahead for wholesale or spot markets, to a minute or even second scale for the balancing markets. In the following chapters, we focus on the short-term electricity markets, with a time scale of up to one day ahead. In the future electricity system, with its high share of renewable energy generation, these markets are of major importance for the daily operation of microgrids due to their ability to react to (short-term) fluctuations in PV or wind generation. Apart from the interactions with these national electricity markets, a microgrid (often) also offers the additional opportunity to trade electricity among its members. This approach is commonly known as peer-to-peer (P2P) trading and has started to gain much attention in research in recent years [231]. In the following, we first introduce the traditional electricity markets, which work at a national level, before explaining two types of P2P energy trading.

Day-Ahead Electricity Market

As the name already indicates, decisions within the day-ahead market have to be made on the day before the actual delivery. The electricity can be bought or sold for one-hour time slots, and after the closing of the market at 12:00, the electricity prices are computed based on the bids of the participants. The pricing and allocation mechanism is often based on a double-sided auction [105], however, within the scope of this thesis, we assume that the microgrid is a *price taker*, that is, its bids do not influence the market prices. Therefore, we use price predictions within the various proposed algorithms.

Intraday Electricity Market

Due to the time difference between submitting the market decisions of the day-ahead market and acting accordingly to them, forecasting deviations in production and demand may occur. To be able to react to these changes, the second market is the intraday market. As the name indicates, the time between the closing of the market and the delivery of electricity is much smaller compared to the day-ahead market. In the European Union, intraday markets may differ in the exact time between the closing of the market and the delivery of energy as well as the time slot length. Often, the considered time slot length is 15 minutes, and the time between closing and delivery is between 45 and 5 minutes, depending on the country [194]. This time difference has shortened drastically in the last few years to better align with the fast-changing fluctuations of PV and wind power. Within this work, we assume that the intraday market operates on 15-minute time slots and that electricity for a time slot t can be bought and sold till the end of the previous time slot $t-1$. Thereby, we assume that the time between closing and delivery shortens again.

Balancing Market

The previous two market types have ensured that for each 15-minute time slot, the amount of produced energy is equal to the amount of consumed energy. However, short-term deviations in planned demand or supply may appear and therefore, the third type of market, the balancing market, ensures the balance between demand and supply in (near) real-time. This market is therefore closest to the time of delivery and operates on even shorter time periods to be able to react to imbalances. As such an imbalance between demand and supply directly leads to a deviation in the frequency of the grid, the balancing market operates differently from the previous two markets. Participants within this market are required to keep flexibility in power available, and in case of a frequency deviation, these power reserves are activated and the balancing energy is used to stabilize the grid frequency to its norm again. The European Network of Transmission System Operators (ENTSO-E) hereby differentiates between different levels of frequency deviations, and the participants are compensated for keeping the power reserves, as well as for providing energy in case of an imbalance [194].

Peer-to-Peer Trading

The previous markets are well-established national electricity markets, which were designed mainly for large-scale participants, such as electricity suppliers or the energy-intensive industry. The P2P trading approach on the other hand takes place within a microgrid and enables small-scale end-users, such as individual households to also directly participate in an electricity market. The main idea of the P2P trading is that households with a surplus of electricity can sell their electricity to (neighboring) households with a shortage of electricity. There are multiple ways how to implement such a local energy trading platform [231],

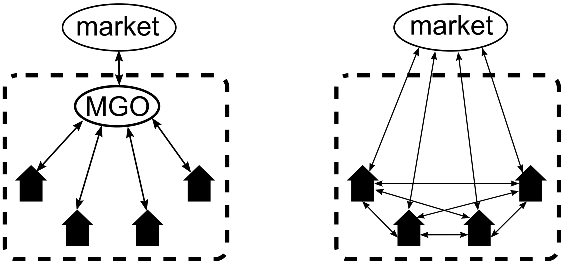


Figure 2.1: Sketch of the *indirect* (left) and *direct* (right) P2P trading approach.

however, one common factor is that the trading scheme allows the participation of users with only little demand or supply. In addition, most P2P trading schemes are restricted to a small area, such as a city. The allocation and pricing mechanisms may differ strongly and can range from duality-based prices to game-theoretic designs.

One central difference between the various P2P trading approaches is the way the actual trading is done, and it can be divided into two general concepts. The *direct* and the *indirect* trading approach.

The main idea of the direct (P2P) trading approach is that households directly trade with each other. That is they (often) negotiate the price and the amount of electricity to exchange with each other. This type of trading allows households to decide with whom to trade and thereby personal preferences can also be included in the trading scheme. Note that in most cases, the overall demand in a microgrid is not equal to the overall supply, and therefore, the households still need to be able to trade with the classical electricity markets.

In the indirect trading scheme, on the other hand, households only interact with the MGO. They communicate their demand or supply to the MGO, which acts as the aggregator within the whole microgrid. In order to balance demand and supply within the microgrid, the MGO can interact with the traditional electricity markets, such as the day-ahead or intraday market. Based on the aggregated demand and supply, the MGO applies some allocation and pricing mechanism and then communicates the results back to the individual households. The market mechanisms may vary strongly, as seen in Chapter 3. In some parts of literature, this type of trading is also known as *community trading*.

2.2.4 Electricity Grid

Connecting the above-presented devices and participants, the underlying electricity grid is enabling the various trading options for households and microgrids. The current (European) electricity grid can be split up into three parts, each responsible for different aspects of electricity distribution and transportation:

- *High-voltage (HV) grid*: The HV grid is responsible for the (long-distance) transportation of electricity from the producers to the consumers and is considered the backbone of (inter)national electricity grids. Mostly large producers and consumers, such as conventional power plants, (off-shore) wind power farms, or electricity-intensive industries are directly connected to the HV grid.
- *Medium-voltage (MV) grid*: The MV grid distributes the electricity within (smaller) regional areas. It connects the HV grid, the low-voltage parts of the grid, and large individual consumers and producers, such as wind power plants, PV farms, or industry with each other. The topology of the grid can range from meshed or ring topologies to radial structures.
- *Low-voltage (LV) grid*: The last part of the electricity grid connects the households within a neighborhood or small village with each other and the MV grid. LV grids usually follow a radial structure and are the most important part of the electricity grid, when focusing on microgrids. As many of the previously introduced changes, such as the electrification of heating or mobility, happen on a household level, the LV grid is particularly affected by the energy transition.

Grid Operator

The operation of the different parts of the electricity grid is managed on two layers:

- *Transmission System Operator:* The Transmission System Operator (TSO) is responsible for the development, maintenance and operation of the national HV grid. Thereby, it enables that electricity can be transported over large distances. In addition, the TSO is also responsible for the grid balance on a national level.
- *Distribution System Operator:* The Distribution System Operator (DSO) operates the regional MV and LV grids. Similar to the TSO, it is responsible for the development, maintenance and operation of the MV and LV grid, and thereby ensures a stable distribution of electricity to the households.

2.3 Mathematical Formulation

In this section, we translate the limitations and opportunities of the devices presented in Section 2.2 into a mathematical formulation. We discretize the considered time horizon into time slots of length Δt. Let $\mathcal{T}$ denote the set of time slots, and let $\mathcal{N}_x$ denote the set of devices of type x.In the following, we first introduce and explain the needed variables, and then proceed to the constraints. We conclude this section with a short introduction to different objective functions.

2.3.1 Variables

In mathematical optimization, the various decisions that can be taken are modeled via decision variables of the formulation. We first introduce device variables, which directly and indirectly model possible actions and decisions for the variables and their consequences on aspects such as the state of charge. Afterward, we introduce the variables representing the interactions with the markets. Hereby, we focus on the exchange with the day-ahead and intraday market.

» $x_{t,j}^{PV} \geq 0$ denotes the energy of the PV system $j \in \mathcal{N}_{PV}$, which is not curtailed during time slot t.

» $x_{t,k}^{B,C} \geq 0$ and $x_{t,k}^{B,D} \geq 0$ denote the charged and discharged energy of battery $k \in \mathcal{N}_B$ within time slot t.

» $x_{t,h}^{EV,C} \geq 0$ and $x_{t,h}^{EV,D} \geq 0$ denote the charged and discharged energy of EV $h \in \mathcal{N}_{EV}$ during time slot t.

» $x_{t,l}^{HP} \geq 0$ denotes the charged electrical energy of the HP $l \in \mathcal{N}_{HP}$ during time slot t. Closely connected, $h_{t,l}^{HP}$ denotes the heating output of the HP within time slot t, while $h_{t,l}^{HP,house}$ denotes the heat taken out of the buffer tank during time slot t to heat the house. Furthermore, $t_{t,l}^{HP,tank}$ denotes the tank temperature of the buffer tank at the beginning of time slot t, while $t_{t,l}^{HP,house} \in \mathbb{R}^4$ is a vector of length four, denoting four different temperature points within the house, see [261] for further details.

» $x_t^{DA,buy} \geq 0$, $x_t^{DA,sell} \geq 0$ denotes the total amount of electricity bought or sold at the day-ahead market for time slot t.

» $x_t^{ID,buy} \geq 0$, $x_t^{ID,sell} \geq 0$ denotes the total amount of electricity bought or sold at the intraday market for time slot t.

2.3.2 Constraints

The variables alone only represent what in general can be done with a device, however, most of these actions are limited by the way the devices work. These additional limitations are modeled via mathematical constraints. Once again, we first focus on constraints derived by the individual devices, before focusing on market and grid-oriented constraints.

PV Constraints

The PV constraint (2.1) ensures that the amount of electricity used from PV j during time slot t does not exceed the PV production $p_t^{PV,j}$,

$$0 \leq x_t^{PV,j} \leq p_t^{PV,j} \quad \forall t \in \mathcal{T}, j \in \mathcal{N}_{PV}. \tag{2.1}$$

Battery Constraints

Constraint (2.2) ensures that the energy within battery $k \in \mathcal{N}_B$ is always between 0 and its total capacity $C^{B,k}$. Let $\eta^{B,k}$ denote the charging and discharging efficiencies of the battery and let $E^{B,k}$ denote the energy in battery k at the beginning of the time horizon. Thereby, the losses due to charging and discharging are already included. Constraints (2.3) and (2.4) limit the charging and discharging for each time slot t to the maximal charging, respectively discharging power $L^{B,k,C}$ ($L^{B,k,C}$). This model is a slightly adapted version of the well-known SoC book-keeping model, see e.g., [139]:

$$0 \leq E^{B,k} + \sum_{s=1}^{t} \left(\eta^{B,k} x_{C,s}^{B,k} - \frac{x_{D,s}^{B,k}}{\eta^{B,k}} \right) \leq C^{B,k} \qquad \forall t \in \mathscr{T}, \tag{2.2}$$

$$0 \leq x_{C,t}^{B,k} \leq L^{B,k,C} \qquad \forall t \in \mathscr{T}, \tag{2.3}$$

$$0 \leq x_{D,t}^{B,k} \leq L^{B,k,D} \qquad \forall t \in \mathscr{T}. \tag{2.4}$$

EV Constraints

Due to the similarities between an EV $h \in \mathcal{N}_{EV}$ and a battery, the constraints and used parameters are rather similar to each other. The additional parameter $p_s^{EV,h}$ in constraint (2.5) defines the energy demand of EV h during time slot s. Constraint (2.8) ensures that an EV $h \in \mathcal{N}_{EV}$ can only be charged or discharged when it is connected to the grid. $\mathscr{I}(h) \subset \mathscr{T}$ denotes the set of time slots when EV h is not available for charging or discharging.

$$0 \leq E^{EV,h} + \sum_{s=1}^{t} \left(\eta^{EV,h} x_{C,s}^{EV,h} - \frac{x_{D,s}^{EV,h}}{\eta^{EV,h}} - p_s^{EV,h} \right) \leq C^{EV,h} \qquad \forall t \in \mathscr{T}, \tag{2.5}$$

$$0 \leq x_{C,t}^{EV,h} \leq L^{EV,h,C} \qquad \forall t \in \mathscr{T}, \tag{2.6}$$

$$0 \leq x_{D,t}^{EV,h} \leq L^{EV,h,D} \qquad \forall t \in \mathscr{T}, \tag{2.7}$$

$$x_t^{EV,h} = 0 \qquad \forall t \in \mathscr{I}(h). \tag{2.8}$$

HP Constraints

The considered HP model, proposed in [261], can be split up into three parts: The HP, the hot water buffer tank, and the house. The model of the HP contains the transformation of electrical energy to heat energy (2.9) using the *coefficient of performance* $COP(t_t^a, t_{set}^{tank})$, which depends on the outside temperature t_t^a and the desired temperature of the tank t_{set}^{tank}. A capacity limit C^{HP} restricts the amount of heat energy per time slot, see constraint (2.10). The buffer tank part only accounts for the changes in temperature in the tank, which depend on physical parameters of water $c_{p,water}$, as well as the mass of water in the tank m_{tank}, see constraint (2.11). In addition, we consider upper and lower limits

$u_t^{HP,tank}$ ($l_t^{HP,tank}$) of the tank temperature (2.12). The house model considers the thermo-dynamics of the household based on the heat input into the house, the individual parameter of insulation of the house as well as time-dependent parameters, such as the sun's influence on the house's heating (2.13). The thermo-dynamic changes are modeled utilizing a linear function $f(\cdot)$. In addition, the user-dependent upper and lower house temperature limits $u_t^{HP,house}$ ($l_t^{HP,house}$) are modeled (2.14) and may differ between households:

$$x_t^{HP} = \frac{h_t^{HP}/900}{COP(t_t^a, t_{set}^{tank})} \qquad \forall t \in \mathcal{T}, \qquad (2.9)$$

$$h_t^{HP} \leq C^{HP} \qquad \forall t \in \mathcal{T}, \qquad (2.10)$$

$$t_{t+1}^{HP,tank} = t_t^{HP,tank} + \frac{h_t^{HP} - h_t^{HP,house}}{m_{tank} c_{p,water}} \qquad \forall t \in \mathcal{T}, \qquad (2.11)$$

$$l_t^{HP,tank} \leq t_t^{HP,tank} \leq u_t^{HP,tank} \qquad \forall t \in \mathcal{T}, \qquad (2.12)$$

$$t_{t+1}^{HP,house} = f(t_t^{HP,house}, h_t^{HP,house}, house) \qquad \forall t \in \mathcal{T}, \qquad (2.13)$$

$$l_t^{HP,house} \leq t_t^{HP,house} \leq u_t^{HP,house} \qquad \forall t \in \mathcal{T}. \qquad (2.14)$$

Demand-Supply-Balancing Constraints

Constraint (2.15) ensures that the sum of supply and demand of the considered devices and market match with the sum of household demands $p_t^{L,i}$ for all time slots $t \in \mathcal{T}$,

$$\begin{aligned}&\sum_{j \in \mathcal{N}_{PV}} x_t^{PV,j} - \sum_{k \in \mathcal{N}_B} \left(x_{C,t}^{B,k} - x_{D,t}^{B,k}\right) - \sum_{h \in \mathcal{N}_{EV}} \left(x_{C,t}^{EV,h} - x_{D,t}^{EV,h}\right) + \\ &x_t^{DA,b} + x_t^{ID,b} - x_t^{DA,s} - x_t^{ID,s} = \sum_{i \in \mathcal{N}_P} p_t^{L,i} \quad \forall t \in \mathcal{T}. \qquad (2.15)\end{aligned}$$

Grid Constraints

For the majority of this thesis, we simplify the grid constraints to a capacity limit at the grid connection of the microgrid to the main grid. Constraints (2.16) and (2.17) therefore ensure that the traded amount of electricity is bounded by the grid capacity C^{grid},

$$x_t^{DA,b} + x_t^{ID,b} \leq C^{grid} \qquad \forall t \in \mathcal{T}, \qquad (2.16)$$

$$x_t^{DA,s} + x_t^{ID,s} \leq C^{grid} \qquad \forall t \in \mathcal{T}. \qquad (2.17)$$

2.3.3 Objectives

The objective of the microgrid can vary depending on the goals of the households or the MGO. It can range from simple minimization of costs or CO2 emissions to maximization of self-consumption of the PV generation or more complex (multi-)objectives. In the following, we present the objective of minimizing the total costs of the microgrid as an example:

$$\min \sum_{t \in \mathcal{T}} \pi_t^{DA}(y_t^{DA,b} - y_t^{DA,s}) + \pi_t^{ID,b} x_t^{ID,b} - \pi_t^{ID,s} x_t^{ID,s}, \tag{2.18}$$

whereby π_t^{DA} corresponds to the (estimated) day-ahead market price for time slot t, and $\pi_t^{ID,b}$ ($\pi_t^{ID,s}$) represent the buying, respectively selling prices of the intraday market for time slot t.

2.3.4 Limitations of the Models

The above-presented model is a simplification of reality. Some limitations of the chosen formulations compared to other models in literature should however be discussed:

» We do not consider losses of energy or heat over time in the battery, EV, or HP and also assume that charging and discharging efficiencies are constant and independent of the state of charge of the battery (EV). These assumptions are common and widespread within the literature (see also [139]).

» Another aspect, which we do not consider is the degradation or life time of batteries or EVs. The life time of a battery depends mostly on two aspects of the operation. The first aspect concerns the frequency of charging and discharging actions, while the second one focuses on the depth of discharge. Current battery technology often allows for a life time of over 2000 charging and discharging cycles, before the capacity decreases below 80% of the initial capacity. As we only consider short time horizons within this work, we assume that the capacity is fixed and does not decrease due to charging and discharging. One way how to include the degradation into the decision-making process is by means of additional costs for charging or discharging the battery or EV.

» The battery and EV models allow charging and discharging during the same time slot. Assuming equal charging and discharging energy limits, we can replace constraints (2.3) and (2.4) by

$$0 \leq x_{C,t}^{EV,k} + x_{D,t}^{EV,k} \leq CL^{B,k}, \tag{2.19}$$

and ensure that the absolute amount of charged and discharged energy does not exceed the limit. Given that the time slot length Δt is usually assumed to be 15 to 60 minutes, the restriction of only allowing charging or discharging may seem overly restrictive.

» The grid constraints as modeled using constraints (2.16) and (2.17) focus only on the connection point of the microgrid to the main grid. Thereby, all power flow equations within the LV grid connecting the households of the microgrid are ignored. Several power flow formulations, such as the AC power flow, the (linearized) DistFlow, or the DC power flow, which better represent the flow of power through the LV grid exist. However, we only consider such a more detailed power flow in Chapter 6, which explicitly focuses on this aspect of local energy trading.

2.4 Solution Techniques

Depending on the exact setting and context of the considered energy management or trading problem, various solution approaches can be applied to achieve an (optimal) solution. The setting and context may define whether the approach should be solved in a centralized or decentralized structure, in which the algorithms try to solve one (common) objective, or whether an individual-based solution structure, in which each participant tries to achieve their own objective, is used. Depending on this, there exist several well-known techniques from optimization theory and game theory to solve such problems.

2.4.1 Decentralized Optimization Techniques

In this section, we present some well-known and established decentralized optimization techniques, which have successfully been applied to solve problems in the energy domain.

Alternating Direction Method of Multipliers

A popular decentralized technique is the *Alternating Direction Method of Multipliers* (ADMM), which solves convex optimization problems by decomposing the problem into subproblems and solving these sequentially. The algorithm is applicable to optimization problems of the form

$$\begin{aligned} &\min f(x) + g(z) \\ &\text{s.t. } Ax + Bz = c, \end{aligned}$$

where x and z are vectors of variables, A, B and c given matrices or vectors, and f and g given convex functions. The augmented Lagrangian of this problem is

$$L_\rho(x,z,y) = f(x) + g(z) + y^T(Ax + Bz - c) + (\rho/2)||Ax + Bz - c||_2^2,$$

with $\rho > 0$. This function is minimized in an iterative approach, where, instead of optimizing over x and z at once, these vectors are updated one after the other, leading to the term *alternating direction*. The corresponding iterative steps are

$$\begin{aligned} x^{k+1} &:= \operatorname{argmin}_x L_\rho(x, z^k, y^k), \\ z^{k+1} &:= \operatorname{argmin}_z L_\rho(x^{k+1}, z, y^k), \\ y^{k+1} &:= y^k + \rho\left(Ax^{k+1} + Bz^{k+1} - c\right). \end{aligned}$$

Regarding convergence rates, there are many different results in the literature. One very general assumption, which is often made, is that the functions f and g are closed, proper, and convex. This assumption implies that the iterative subproblems of determining x^{k+1} and z^{k+1} are solvable. In practice, ADMM often converges fast to a moderate level of accuracy but afterward shows slow converging behavior to high accuracy. See [37] for a detailed and in-depth analysis of ADMM, including both, theoretical and practical results.

Consensus and Innovation

Another class of decentralized optimization techniques, which has been successfully used in the energy domain, are variants of *Consensus and Innovation* (C+I) [230] or decentralized versions of primal-dual gradient methods [131]. These decentralized optimization techniques are applied by modeling the trading system using various mathematical formulations such as e.g., an LP, MILP, or MIQP. The arguably most important step here is to formulate the problem in such a way, that the formulation can be decomposed into subproblems. These subproblems hereby often represent the problem of energy scheduling for a single prosumer, which then can solve its own (sub)problem using standard optimization techniques, such as interior point methods or the Simplex algorithm. Several of the above-mentioned techniques rely on a master problem which coordinates the process of solving the overall problem. This master problem is often solved by the MGO and together with the subproblems being solved by the prosumers, this is a quite natural representation of the structure of the underlying microgrid. These approaches also show similarities to the Stackelberg games, in which the prosumers solve their own problems and communicate their solutions to the MGO, which in turn updates and sends prices or other steering signals.

2.4.2 Game-Theoretic Solution Concepts

In this section, we present some concepts from the research field of game theory, which deals with mathematical models and concepts for the strategic behavior of rational players. A common division of game theory is into the areas of cooperative and non-cooperative game theory.

As the name already hints, cooperative game theory deals with aspects related to coalitions of players, such as the allocation of profit of cooperation among all participating members. Often, the main focus is on finding such an allocation that makes the coalition of all players stable, meaning that no subset of members has an incentive to leave the coalition.

Non-cooperative game theory, on the other hand, focuses on the behavior of players who compete with each other. Concepts such as an equilibrium, which is a situation where no player can be better off by deviating, are the main foundation for determining allocations.

A further important area, which lies in the intersection of game theory and optimization is mechanism design, which focuses on designing market rules to ensure socially desirable outcomes. These concepts are explained in more detail in the following three subsections.

Cooperative Game Theory

Starting with techniques from cooperative game theory, we introduce the concepts of the core and the Shapley value. Given a coalition game $\Gamma = (N, v)$, with N being the set of players, in our case the prosumers, and $v : 2^N \to \mathbb{R}$ being the value function, assigning a value $v(S)$ to each subset of players $S \subseteq N$, the main question of cooperative game theory is how to allocate the value of a coalition to its members. In the area of energy trading, the value function $v(S)$ could correspond to the value of the energy savings of a coalition S given that prosumers in S cooperate with each other e.g. by trading or using batteries. Let $x \in \mathbb{R}^{|N|}$ denote an allocation with x_i being the share of player $i \in N$. An allocation x is called *feasible* if $\sum_{i \in N} x_i \leq v(N)$, that is the allocation distributes not more than the value of the grand coalition N. The allocation can be seen as the distribution of the overall savings of all prosumers among themselves.

The Shapley value is one of the most well-known concepts in cooperative game theory. Its main goal is to characterize a *fair* allocation of value to the players. It is based on the following three axioms:

» *Symmetry*: For all $i, j \in N$, where $v(S \cup \{i\}) = v(S \cup \{j\})$ for all $S \subset N$ with $i, j \notin S$, the allocations are equal, that is $x_i = x_j$.

» *Dummy player*: A player is a dummy player if she always adds the same amount of value to any coalition she joins, i.e. for all S with $i \notin S$ we have $v(S \cup \{i\}) - v(S) = v(\{i\})$. The allocation for a dummy player is then $x_i \coloneqq v(\{i\})$. This axiom is sometimes also known as the *null player* axiom.

» *Additivity*: For two games $\Gamma_1 = (N, v)$, $\Gamma_2 = (N, w)$ over the same set of players N, and the game $\Gamma_3 = (N, (v + w))$, defined by $(v + w)(S) \coloneqq v(S) + w(S)$ for all $S \subseteq N$, the allocation for each player for game Γ_3 has to be equal to the sum of the allocations for the two games Γ_1 and Γ_2, i.e. we have $x_i((v + w)) = x_i(v) + x_i(w)$.

In [220], Shapley specified an allocation scheme satisfying all these three axioms. In addition, it was shown that this is the unique allocation x satisfying efficiency, that is $\sum_{i \in N} x_i = v(N)$. The Shapley value of player i for a game $\Gamma = (N, v)$ is given by

$$x_i \coloneqq \frac{1}{|N|!} \sum_{S \subseteq N \setminus \{i\}} |S|!(|N| - |S| - 1)! [v(S \cup i) - v(S)].$$

It can be seen as the average marginal contribution of player i to any coalition. Taking a closer look, we see that in order to compute the Shapley value using this formula we need to consider every subset at least once. Therefore for general coalition games, the running time to compute the value in this way is exponential in the number of players. Nevertheless, there are approaches to deal with the running time, for example by approximating the value using (random) subsets of the coalitions of the players. Furthermore, for some special value functions, there also exists closed-form formulations that can be computed efficiently.

While the Shapley value is seen as fair and always exists for any coalition game, the question arises whether this allocation is also *stable*. The stability of an allocation is related to the question of whether subsets of agents could get better off by forming smaller coalitions on their own. One concept that deals with the stability of an allocation is the core, which is the set of stable allocations. An allocation x is stable and therefore in the core of a game $\Gamma = (N, v)$, if and only if

$$\sum_{i \in S} x_i \geq v(S), \quad \forall S \subseteq N.$$

In practical applications, this is a desirable property, as a stable allocation ensures that no subset of players would have an incentive to deviate from the grand coalition. One important question is whether there always exists an allocation in the core. The answer to this is 'no', meaning there are games with an empty core, implying that there is no allocation to the players that is stable. For games with a non-empty core, the next interesting problem is if the Shapley value always lies within the core. Once again the answer to that question is 'no', as there are games where the core is non-empty, but the Shapley value is not part of it. In [149] some examples of such games are given. However, there are also classes of games, for which the Shapley value always lies within the core. One such class of games, which are not so rare in practice, are *convex games*, where the value function v is *supermodular*. Therefore, showing that the value function is supermodular directly implies that the core exists and that the Shapley value lies within. See also Chapter 8 in [149] for a concise, but detailed introduction to the area of cooperative game theory.

Non-cooperative Game Theory

In this section, we consider the research field of non-cooperative game theory. A (finite) normal-form game is defined by a triple $\Gamma = (N, \mathcal{A}, u)$, with N being a (finite) set of players i, $\mathcal{A} = \mathcal{A}_1 \times \mathcal{A}_2 \times \ldots \mathcal{A}_n$ the set of available actions, with $\mathcal{A}_i$ being the action space of player i, and $u : \mathcal{A} \to \mathbb{R}^n$ the utility function, mapping a feasible strategy $s \in \mathcal{A}$ to its value $u(s)$. Hereby, the i-th entry of $u(\cdot)$ represents the utility of player i. In the context of local energy trading, the set of players may represent the set of prosumers of the microgrid, and the action space $\mathcal{A}_i$ of player i may represent the possible actions and decisions of prosumer i during a given time horizon $\mathcal{T}$. Often this translates to energy schedules specifying for each time slot t the usage of energy due to devices such as EVs or batteries. The utility function $u_i(s)$ in the game represents the utility function of prosumer i. In most cases, the utility function is a combination of the cost of energy given the profile s and the preferences of a prosumer w.r.t. its energy usage. There are two solution strategies for the players:

» *Pure strategy*: Each player i chooses a pure action $a_i \in \mathcal{A}_i$.

» *Mixed strategy*: Each player i randomizes over her set of available actions following some probability distribution. A mixed strategy of player i is specified by a vector $s_i \in \mathbb{R}_{\geq 0}^{|\mathcal{A}_i|}$ with $\sum_{a_i \in \mathcal{A}_i} s_i(a_i) = 1$ and $s_i(a_i)$ the probability that action a_i is chosen by player i. We denote the space of all mixed strategies of player i by S_i.

Note that a pure strategy is also a mixed strategy with all probability on one action. In contrast to the above definition, in the energy trading context, a mixed strategy can be seen as a convex combination of multiple (pure) strategies rather than a probability distribution, as each pure strategy corresponds to an energy usage profile that can be combined with each other. In a general game Γ, this may not be possible and therefore the terms of mixed and pure strategies are used. The (expected) utility of a strategy s for player i is given by

$$u_i(s) = \sum_{a \in \mathcal{A}} u_i(a) \prod_{j=1}^{n} s_j(a_j).$$

If the game has only 1 player, this player can directly decide whether a strategy is optimal or not. However, in general, player sets are larger and we need another way to evaluate a strategy. To deal with this, we introduce one of the arguably most important solution concepts in game theory, namely the Nash equilibrium (NE). A strategy profile $s = (s_1, s_2, \ldots, s_n)$ is called a NE, if and only if for all players i

$$u_i(s_i, s_{-i}) \geq u_i(s_i^*, s_{-i}) \quad \forall s_i^* \in S_i,$$

where s_{-i} is the strategy profile s without the strategy of player i. Referring back to the situation of energy trading, strategy profile s is a NE, if and only if no prosumer i can improve her utility (function) by deviating from s_i given that all other prosumers still act according to s_{-i}. In [186], Nash introduced his idea and showed that for every finite n-player game, there exists a mixed NE.

One popular game used for modeling markets is the *Stackelberg game*. It is often used for oligopoly models, where one player moves first, and the other players can observe this move and then decide on their actions. The player moving first is called the *leader* of the game, and the remaining players are the *followers*. Depending on the exact setting of a Stackelberg game there either exists a closed-form solution or an iterative approach converging towards the Stackelberg NE. In the context of energy trading or energy management systems, the leader is often the MGO, or another third entity independent of the prosumers, such as a DSO. The utility function of this leader is then related to grid constraints, such as minimizing peaks and its action space consists of setting energy prices for the prosumers. The followers are the prosumers, who, based on the decision of the MGO, try to maximize their own utility. They then report their resulting power profile back to the MGO, which can either react by updating the prices (increasing prices during times of peaks) and thereby entering the next iteration or by accepting the actions of the prosumers. The resulting solution is a Stackelberg NE that ensures that neither the prosumers nor the MGO can be better off by deviating from the chosen actions.

Mechanism Design

The research area of (algorithmic) mechanism design lies within the intersection of game theory and optimization. Its goal is to design algorithms or rules that ensure a socially desirable outcome in settings with selfish decision-making agents having individual preferences. Examples of such settings include various auctions, voting systems, cost-sharing mechanisms, or matchings.

The difference between a mechanism design and an optimization viewpoint is that in mechanism design the agents cannot directly be forced to reveal their preferences. In addition, agents may try to manipulate the outcome by revealing false preferences, and they may not have an incentive to accept the outcome. The main challenge now is to design the algorithm such that the individual objectives of the agents align with the overall goal of the socially desirable outcome. Often, the algorithm can be split up into two parts, namely the assignment and the payment scheme. The goal of the assignment scheme is to efficiently find a socially desirable solution assuming that the agents reveal their true valuation. The payment or incentive scheme then needs to be designed in such a way that revealing the true preferences always results in the best outcome for each agent.

In the following, we use the example of a *second-price sealed bid* auction to highlight how assignment and payment schemes can look like. We also shortly introduce other types of auctions without going into the details of the algorithms.

In the second-price sealed bid auction, an auctioneer wants to sell only one item. The set of agents is the set of possible buyers, each with a private valuation of the item. The utility function of an agent i is either 0 if agent i does not get the item after the auction, or it is its valuation minus the price paid for the item. The socially desirable outcome for the auctioneer is to sell the item to the agent with the highest valuation. During the auction process, each agent can submit a value, representing its public valuation, without the remaining agents knowing the value. Note, that the bid is not necessarily equal to the private valuation. The auctioneer then declares the agent with the highest bid the winner (assignment scheme) and charges as the price the second highest bid to the winner (payment scheme). It can be shown that for each agent, truthfully submitting its private valuation is a dominant strategy. This property is often referred to as *dominant-strategy incentive compatible* (DSIC). Thus, agents cannot improve their utility by misreporting their valuation, and due to the structure of the payments, they also have an incentive to accept the outcome.

The Vickrey-Clarke-Groves (VCG) mechanism is a generalization of the above auction setting and is able to select any socially desirable solution out of a set of feasible solutions while being truthful. It can also be applied to other auction settings such as the *double auction*, which is a two-sided auction. In two-sided auctions, the set of agents can be split into two subsets, namely the sellers and the buyers. Bids now consist of two values, the first one is the number or amount of items, in our case, electricity, which they either want to buy or sell. The second value is the price they are willing to pay or the price they want to receive. McAfee [174] proposed a truthful mechanism for two-sided auctions which ensures that the payments received by the sellers are equal to the payments made by the buyers, a property which the VCG mechanism applied to this setting is not able to guarantee. Other variants of two-sided auctions are *continuous double auctions*, in which bids arrive over time and after each arrival, the auctioneer checks for possible trades. For an in-depth review of different truthful mechanisms as well as a theoretical introduction to mechanism design see [192], in particular chapters 9 to 16.

In the area of energy trading, two-sided auctions, such as (continuous) double auctions have been applied for matching demand and supply. The players are the prosumers with either a surplus (seller) or a demand (buyer) of energy, as well as a private valuation of energy. The solution is then a set of players who trade with each other instead of selling to or buying from the electricity market.

Another approach from mechanism design, which is used for energy trading is called *cake-cutting*. The problem is to divide an infinitely divisible set of heterogeneous resources among a set of players. The main difference to other allocation problems in game theory, such as the core or Shapley value, is that the players have individual value functions u_i over the set of resources. As players are selfish, the task is to divide the resources such that the assignment is seen as fair by every player. There are several notions that are related to the term fairness, but for cake-cutting, a mechanism to divide the resources is *proportional*, if for each player its piece is at least as valuable as the value of the complete resource divided by the number of players. A mechanism is said to be *envy-free* if for each player its own piece is at least as valuable as the piece of any other player. Both proportionality and envy-freeness are popular properties of fairness, see [39]. In the area of energy trading, cake-cutting games have been used to split up the budget of an MGO for buying energy from its prosumers using different prices [255].

3 Classification of local energy trading

Abstract – *This chapter provides an overview of the current state of research within the area of local energy trading and management. First, various aspects, which should be considered when classifying the body of literature, are introduced. Based on these aspects and characteristics, a review of the current state of literature is done. The findings are represented by three main lines of research with a total of five clusters of approaches, each with its own unique combination of characteristics. Each cluster is presented in detail and connections between the individual clusters are analyzed. This chapter concludes with a detailed explanation of aspects which have mostly been neglected in energy trading literature.*

3.1 Introduction

As already introduced in Chapter 1, in the last few years, the energy transition has gained significant attention, both in practice and in academia. The academic literature on this topic mostly focuses on various control, management, and trading algorithms using the potential flexibility offered by smart devices to ensure a stable electricity distribution in the future. Historically, energy trading has always happened on national electricity markets, such as the day-ahead or intraday wholesale market, as introduced in Section 2.2. However, due to the drastic changes to the energy system, new, local trading and market approaches, which include small-scale households as participants, need to be considered and are therefore a key focus in the literature.

The field of traditional energy markets has always attracted the attention of researchers from different areas, such as electrical engineering, operations re-

This chapter is based on [JH:1].

search, or (power) economics. This research considered amongst others, variations of the classical unit commitment problem (see e.g., [17, 27, 119, 241]), bidding or pricing strategies for different national electricity markets (see e.g., [2, 3, 5, 40, 41]), load forecasting (see e.g., [95, 107, 158]), AC or DC optimal power flow computations (see e.g., [31–33, 227]) or cascading failures and blackouts in high-voltage grids (see e.g., [24, 29, 30, 189]). Compared to these problems, local energy trading focuses on the LV grid and offers new, interesting challenges, such as congestions in LV grids due to the increased demand and local generation, or the impact of prosumers' behavior, which is not necessarily restricted to cost savings or profit maximization. Hence, existing techniques and approaches used on a national level cannot simply be transferred to the local level, but need to be adapted and newly implemented.

The main contribution of this chapter is twofold. In a first step, we provide a detailed overview of existing literature in the area of local energy trading. Due to the wide range of settings and research questions in publications in this field, we first identify and define various characteristics and research questions related to the settings. Based on these questions and characteristics, we classify the considered literature into three main clusters and analyze each cluster on its own. During this analysis, we compare the used techniques within each cluster, as well as investigate possible connections between the clusters. In a second step, we identify open questions and challenges in local energy trading, based on the insights gained from the analysis. To the best of our knowledge, many of these interesting open challenges have been neglected up to now.

3.2 Classification Approach

Given the wide range of different settings and research questions in the considered literature, we first cluster similar problem settings together and then compare the clusters with each other. In order to cluster the settings, we first need to identify and define the key characteristics as well as the high-level research questions. Combining own findings as well as some of the characteristics found in [130] and in [260], the final classification scheme is based on the following characteristics:

1. *Valuation*: Is the valuation of electricity of each prosumer taken into account? The valuation can be represented by means of bids in an auction approach or by utility functions in (non-)cooperative games. Utility functions are often a weighted sum of different aspects of electricity consumption, such as the cost of purchase, the profit of selling electricity, or the satisfaction of (the results of) electricity consumption.

2. *Flexibility*: What kind of flexibility w.r.t. electricity consumption and generation is taken into account? This can span from no flexibility over flexibility due to the usage of a battery or EV to flexible load and curtailment of PV generation.

3. *Structure*: How is the computation organized? Is it done centrally by the MGO or are computations distributed among all participants?
4. *Objective*: What is the main objective of the setting? The objectives in the considered literature range from maximizing social welfare, over minimizing costs to minimizing peak load or maximizing local consumption.
5. *Stability and Fairness*: Should the solution be stable against strategic manipulation of participants? Is the solution fair to everyone? As there is no common scientific definition of fairness, it refers to the lack of discrimination of a subset of the prosumers within assignments or decisions taken by the algorithms.
6. *Participants and their incentives*: Which entities can participate in the local energy trading scheme? Do all participants profit from the local energy trading scheme or may some participants be off the same as when not joining the energy trading scheme?

Using these characteristics, the final classification scheme consists of three major clusters, each with a unique setting and high-level research question. Two of the major clusters can be further split into two subclusters each. The reason for maintaining such a structure with three main clusters and two of them consisting of two subclusters each is that the two subclusters are very similar to each other, meaning that they are much closer related to each other than to any other cluster. Hence, we keep the three main clusters, each with a clear focus on the setting and problem definition, but also acknowledge the smaller but still noticeable differences within two of the clusters. We refer to Table 3.1 for an overview of the relation between the different clusters and the considered characteristics.

The first identified cluster consists of settings in which the valuation of electricity of each prosumer is taken into account in the form of a bid. Demand and supply are fixed and smart devices do not offer any flexibility. Only prosumers are considered participants in this cluster and no participant is worse off compared to not joining the proposed energy trading schemes. The high-level research question in this setting is to match fixed demand and supply with each other while maximizing the social welfare of the participants. In the following, we refer to this cluster as the *Matching without Flexibility* cluster. A closer analysis of the settings in this cluster reveals that it can be split further into two subclusters. In the first subcluster, all computations are done centrally, and, assuming rational participants, the solution is protected against strategic manipulations. In addition, not all participants need to profit from participating. This subcluster is referred to as the *Strategic Matching without Flexibility* cluster. In the second subcluster, on the other hand, computations may be done in a decentralized way, but there is no guarantee that the solution is stable. Given some (light) assumptions, all participants may profit from their participation. We refer to this subcluster as the *Direct Matching without Flexibility* cluster.

The second cluster does not take the valuation of prosumers of electricity into account. Instead, its goal is to minimize the overall costs of a given set of prosumers and divide the cost among the participants. Demand and supply are fixed, but in some cases, flexibility is offered by batteries. The computation is done centrally, and the distribution of the cost should be done fairly and in such a manner that no group of participants has an incentive to deviate from the centrally managed solution. The high-level research question is to find a pricing scheme, such that every prosumer benefits from following the optimal solution. For the remainder of this work, we refer to this second cluster as the *Cooperative Pricing Scheme* cluster.

The third cluster encompasses settings in which flexibility is offered by smart devices, such as batteries, EVs, or heat pumps, but also by flexible parts of the load. Participants can include a wide range of entities, from prosumers to companies or aggregators. The valuation of electricity is usually taken into account in the form of a utility function, often as a weighted sum of different objectives. Computations are done in a decentralized way, usually mimicking the underlying structure of the participants. The focus of the high-level research question is to locally balance consumption and generation using the given flexibility while maximizing social welfare. In the following, we refer to this cluster as the *Balancing with Flexibility* cluster. Similarly to the *Matching without Flexibility* cluster, we again can split the cluster into two subclusters, each with its own focus. In the first subcluster, the whole group of participants shares a common objective, usually the sum of the utility functions of all participants. The main goal is then to find an optimal solution that maximizes (or minimizes) the objective. We refer to this subcluster as the *Joint Balancing with Flexibility* cluster. The other subcluster on the other hand treats every single participant as an individual, selfish agent who wants to maximize its own utility. In this setting, the objective is to find an equilibrium solution in which no participant can improve its utility by deviating from this solution. In the following, we refer to this cluster as the *Equilibrium Balancing with Flexibility* cluster.

At the start of our research, we considered in addition to characteristics 1 to 6 also the following characteristics for the classification scheme. However, the additional characteristics were not selected because either they did not add any further insights into the clusters, or the resulting (sub)clusters were too small and the differences between subclusters were only present in one single aspect.

7. *Devices:* What kind of (smart) devices, such as PV systems, batteries, EVs, or HPs are considered in the approach?
   Within the scope of local energy trading, we are much more interested in the flexibility the devices can offer compared to the management of the devices themselves. Hence, the actual devices are not important, but only the (type of) flexibility they can offer.
8. *Time Horizon:* What is the considered time horizon of the setting? Are multiple time slots considered at once or only one single time slot after the other?
   The characteristic of time horizon is only important in the presence

	MF			BF	
Characteristics	SMF	DMF	CPS	JBF	EBF
Valuation:					
- bids	x	x	-	-	-
- utility function	-	-	-	-	x
Flexibility:					
- battery	-	-	x	x	x
- demand	-	-	-	x	x
- supply	-	-	x	x	x
Structure:					
- centralized	x	x	x	-	-
- decentralized	-	-	-	x	x
- hybrid	-	x	-	x	x
Objective:					
- max social welfare	x	x	-	-	x
- min total cost	-	-	x	x	-
Stability and Fairness:					
- stability	x	-	x	-	x
- fairness	-	-	x	-	-
Participants and Incentives:					
- participants	all	all	all	all	all
- incentives	x	x	x	-	x

Table 3.1: Overview of the relation between the different clusters and the characteristics; Matching without Flexibility (FM), Balancing with Flexibility (BF), Smart Matching without Flexibility (SMF), Direct Matching without Flexibility (DMF), Cooperative Pricing Scheme (CPS), Joint Balancing with Flexibility (JBF), Equilibrium Balancing with Flexibility (EBF))

of smart devices, such as batteries or EVs, which can shift energy demand through time. Within each of the three main clusters, either all approaches have the same time horizon, or approaches covering one time slot do not consider the flexibility of such smart devices, and therefore each time slot can be optimized individually.

9. *Grid Constraints:* Are grid constraints considered in the problem definition?
Due to an increase in electrification of mobility and heating as well as local electricity generation, congestion in LV grids or other violations of (LV) grid constraints are becoming more likely and hence pose a serious threat to the reliability of future electricity distribution.
However, grid constraints are rarely taken into account in the considered approaches. Hence, the resulting subclusters, which do take grid constraints into account, only consist of one or two approaches, and therefore can rather be seen as outliers than as actual clusters that offer further insights into the underlying structure of local energy trading.

10. *Uncertainty:* Is uncertainty taken into account?
    In particular, in settings with a larger time horizon, forecasts and predictions of load and generation are often not perfect. PV generation heavily depends on the weather, while the household load is subject to the prosumer's decisions and behavior. Both, human behavior, as well as the intermittent generation of renewable energy sources, are known to be difficult to predict.
    While it is reasonable to assume that in settings with only one time slot, uncertainty does not play a large role due to the short time horizon, most settings with larger time horizons also do not consider uncertainty in predictions and forecasts. Similar to the grid constraints, the resulting subclusters would be very small and not yield any additional insights into local energy trading.

3.3 Clusters

Based on the introduced general framework and the different techniques, we now study the introduced classification scheme in detail. We first describe the settings within each cluster and then analyze and compare the different techniques used within each cluster.

3.3.1 Matching without Flexibility

Strategic Matching without Flexibility

As briefly described in Section 3.2, the Strategic Matching without Flexibility cluster is one of two clusters that mainly focuses on matching prosumers to each other. Even beyond the considered characteristics 1 to 6, the settings are all very similar to each other. If devices, such as PV or batteries, are considered, they are usually not controlled within the scope of the used techniques, but rather change the demand or surplus of the corresponding prosumers in a fixed and often greedy way, without offering any further flexibility. Corresponding to this general setting of fixed demand and supply, and no flexibility, the considered time horizon usually only covers one time slot. Hence, the research questions aim to match prosumers with each other on rather short notice, such as given in balancing markets. This also aligns with the absence of uncertainty in the data. If the considered time slot is rather short and the computations are done directly before the realization, forecast errors may be reasonably small and can therefore be neglected. Analyzing the approaches within this cluster, it becomes obvious that the used techniques are quite similar and often related to concepts from mechanism design. The techniques can be divided into three groups, namely auctions, non-cooperative games as well as approaches based on matching and contract theory.

Approaches based on auctions, are presented in [36, 47, 88, 127, 128, 215, 238, 257]. In all of these approaches, the prosumers participate in an auction and can be divided into two groups, one with a surplus of and one with a demand for electricity. The outcome of the auction is a subset of the prosumers, which trade with each other, as well as a clearing price and the amount of electricity each prosumer in the subset contributes to the trade. Different types of auctions have been proposed throughout the literature, with the standard double-auction [128, 215, 257] or combinatorial (VCG) auctions [47, 127] as presented in Section 2.4 being the most prominent ones. A very interesting way how to combine heat and electricity into one auction is presented in [215], where the double auction is modified to be run once for both energy types simultaneously. [128] presents a way how to include grid constraints into an auction setting by modifying the pricing mechanism of the double auction to include additional charges based on a linear approximation of active power flow. In [238], the concept of a double auction is used in an online setting, in which both, demand and supply offers may appear and disappear over time. The approach in [272] is based on the same principles as the auctions above, namely individual rationality and incentive compatibility, but makes use of contract theory. All sellers publicly announce their producer type, which contains the amount of electricity to sell and the cost of production. The buyer then uses a mathematical model to find the optimal bids for each type. It is shown that for sellers truthfully reporting their type is a best response strategy.

Different matching approaches are presented in [132] and in [136]. In [132], the matching is done via a priority list which is based on the economic profit of a trade between two prosumers. The negotiation between two matched prosumers is executed as an iterative approach and the final solution is shown to be a NE. In [136], the matching is based on the outcome of the Galey-Shapley algorithm, where the input is a distance measure of the difference between surplus and demand between each pair of prosumers. In this approach, there is no negotiation process as the internal trading price is fixed to a certain fraction of the trading price with the external grid.

In contrast to the previous approaches, the approach in [202] is based on a non-cooperative game. A set of prosumers reports their demand or supply for the coming time slot to the MGO. Based on previous contributions to the microgrid, as well as its current request, the MGO distributes the surplus of electricity to the prosumers with a need. The distribution algorithm is based on a water-filling algorithm, while the strategic choice of how much energy to ask for is decided using a non-cooperative game among the prosumers with a demand for electricity.

Direct Matching with Flexibility

Another way to enable trading between prosumers is to either use continuous double auctions [36, 46, 88, 262] or to match buyers and sellers directly with each other [132, 175]. Using the iterative nature of a continuous double auction, in [36] heat and electricity are traded together. To achieve this, two continuous double auctions are executed in parallel and after each new computation, bundle constraints between heat and electricity are checked. In [88] and in [262], each possible trade is first checked w.r.t. grid violations before it is allowed and congestion prices may be added. In [132] on the other hand, the peer matching algorithm includes the impact of trades for the grid constraints by means of the pricing negotiation. [175] analyses the efficiency of random peer matching on the social welfare. The price negotiation can range from pay-as-bid strategies for the buyers [175] to iterative negotiation algorithms [132], in which both players update their prices until a final price is found. In [176], a comparison between continuous double auctions and random peer-matching algorithms with different price negotiation techniques is presented.

3.3.2 Cooperative Pricing Scheme

As mentioned in Section 3.2, the main research question for the settings in the Cooperative Pricing Scheme cluster is to encourage prosumers to follow the centrally computed solution by creating a pricing scheme from which every prosumer profits. The settings within this cluster are once again very similar to each other, also beyond the considered characteristics. Apart from [147], no approach considers uncertainty in any form, although there are some settings with multiple time slots. Grid constraints are also not taken into account. This may be explained by the settings, where prosumers do not have flexibility in their load to change their demand or surplus. Hence, even without the centrally computed solution, prosumers would still trade the same amount of electricity with the grid. Therefore, no additional problems w.r.t. grid congestion or violation of grid constraints appear. In all settings, some form of renewable energy production, mostly PV generation, is considered. Some of the settings also include batteries, which are usually used to minimize the amount of traded electricity with the grid. The settings with batteries often cover multiple time slots, while most settings with only one time slot do not consider batteries. The main difference between the approaches, which consider only a single time slot at once, and approaches, which consider multiple time slots can be found in the centralized computation, while the pricing scheme is often identical or at least very similar. In general, the used techniques are based on cooperative game theory, in particular the Shapley value and the core.

The approaches, which are directly based on the Shapley value are [54, 58, 97–100, 147, 151, 165, 178, 193, 267]. While [58, 147, 193, 267] cover one only time slot, the remaining approaches solve the centralized problem of minimizing the total cost of the microgrid for a larger time horizon. Combined with batteries, this can further increase the cost saving compared to solutions of individual prosumers. One important aspect to be considered when using the Shapley value is the scalability of the approach. In general, an exponential number of subproblems has to be solved to be able to compute the Shapley value. Hence, for slightly larger microgrids this may already pose a serious problem. Fortunately, only the payments depend on the Shapley value, while the distribution of electricity between the prosumers and devices is the solution to the centralized optimization problem. Hence, the Shapley value may theoretically still be computed even after the considered time horizon. One assumption in this context is that all prosumers will participate in the trading scheme, even without knowing their exact cost savings. Another way to avoid the problem of computational complexity is by approximating the Shapley value, which can be done in various ways [54, 98, 100, 147, 193]. In [100] and [193], a stratified sampling approach is used to reduce the number of subproblems to solve, while in [98] similar prosumer profiles are clustered together to reduce the number of participants and thereby also the number of subproblems to solve. The approach in [147] does not reduce the number of subproblems to solve, but rather computes the asymptotic Shapley value using statistical parameters of the considered uncertainty. In addition, it is shown that the asymptotic Shapley value lies within the core of the cooperative game. An overview over different applications of the Shapley value in the context of energy communities or energy trading is presented in [193].

Another technique used within the Cooperative Pricing Scheme cluster is to show that a tailor-made pricing scheme lies within the core of the cooperative game, and is therefore stable against group deviations. As mentioned before, this is done in [147] for the Shapley value, but also in [178] for a pricing scheme based on the nucleolus and in [256] for the mid-market price. The mid-market pricing scheme simply computes the internal trading price as the average of the buying and the feed-in price of the grid. Based on the common assumption that the feed-in price is strictly smaller than the buying price of the grid, it can be shown that this pricing scheme lies within the core of the game. Apart from the nucleolus and the Shapley value as pricing schemes, in [178] two additional allocation schemes are introduced. The first one is a uniform pricing scheme, while the second one is based on the VCG payment rule. In [164] several pricing schemes are proposed. The first pricing scheme is the mid-market price, which lies within the core, as explained above. The second pricing scheme is based on a double auction, while the third one is referred to as bill-sharing. In this pricing scheme, the single microgrid bill of the overall trade with the external grid is shared among all prosumers using a fixed internal price for buying and selling.

A further technique from cooperative game theory is used in the second step of the two-step optimization approach in [117]. Here, a Nash Bargaining approach is used to decide how the jointly generated cost savings should be distributed among the players.

3.3.3 Balancing with Flexibility

Joint Balancing with Flexibility

The settings within the Joint Balancing with Flexibility cluster deal with the question of how prosumers can make use of their flexibility to optimize a common objective. The settings and approaches within this cluster are all rather similar to each other, although some settings highlight particular aspects, such as the preference between different 'types' of electricity, such as e.g. locally produced or green electricity. Due to the decentralized structure of computation, individual data and parameters of the participants, such as the flexibility or the valuation of electricity, do not need to be shared. Therefore, most settings take data privacy into account. As mentioned in Section 3.2, all of the settings in the Joint Balancing with Flexibility cluster do take flexibility into account. In some settings, this flexibility directly stems from devices such as batteries, EVs, or HPs, but there are also some problem definitions, in which flexibility only stems from the flexible part of the load. These settings often reduce the problem to a bare minimum and do not model devices explicitly. Nevertheless, the models are able to represent the key problems that may occur in (local) energy trading. Regarding the time horizon, some settings directly formulate models for multiple time slots, while quite a few of the considered settings within this cluster only formulate single time slot models. Nevertheless, it is often noted that for the sake of simplicity and notation, only a single time slot is modeled, but the presented approach can easily be adapted for multiple time slots. However, even though larger time horizons can be modeled at once, uncertainty is not taken into account in any of the settings. Grid constraints are also not considered by the majority of settings, although a few use approximations of power flow to create price signals for overloaded lines within the grid. In all settings, decentralized optimization techniques, such as ADMM, relaxed C+I, or decentralized primal-dual algorithms are used.

The approaches in this cluster are [18, 91, 117, 129, 131, 144, 179, 180, 182, 230, 231]. In [18, 91, 144, 179, 180, 230, 231], the approaches are based on simplified and reduced models in which no devices are directly modeled. Nevertheless, different types of local trading, such as direct peer-to-peer trading, communal trading, or a hybrid version are formulated and solved either via ADMM or relaxed C+I, see Section 2.4 for a short introduction to these techniques. Due to the structure of the simplified models, there is no difference in the objective value of the proposed decentralized and centralized optimization algorithms. In addition to an optimal solution, the relaxed C+I in [230] also computes prices for each individual trade, which are based on the economic concept of shadow prices, that are the dual variables of the trade constraints. In [129] and in [131], the same simplified model is extended by grid constraints in the form of distribution load flow. Based on the load flow, the power transmission distribution factor (PTDF), which computes the contribution of each trade between prosumers on the power flow, is computed for each line in the grid and is used as a price signal for the prosumers. Before solving this model with an adapted decentralized primal-dual gradient method, Lagrangian multipliers move global constraints into the objective function. Instead of introducing grid constraints to the simplified models, in [117, 148, 182] different devices, such as batteries are directly modeled. While in [182] prosumer preferences over different classes of electricity, such as green or local electricity, are introduced, in [117] a payment scheme in a second stage, which is based on a Nash Bargaining game, is proposed. All three models are again solved using ADMM. In [180] risk levels for prosumers are introduced to model different human behavior in the presence of uncertainty. The model is again solved using ADMM.

Equilibrium Balancing with Flexibility

Another approach to make use of flexibility is offered by the settings in the Equilibrium Balancing with Flexibility cluster. In contrast to the Joint Balancing with Flexibility cluster, the participants behave more selfishly and do not simply act as distributed computing units for the goal of the whole microgrid. Individual objectives and goals are more important and techniques that lead to stable solutions in which no participant can improve anymore have to be used. Beyond the considered characteristics, for most aspects, there are large similarities between the settings, although there are some exceptions. Comparable with the previous cluster, due to the decentralized structure of computations, in most cases, sensitive data, such as flexibility or utility functions, can remain private for each participant. Apart from [223], no other setting considers grid constraints in its approach. Devices are mostly explicitly modeled, although there are a few settings, in which there are either no devices modeled or PV generation is indirectly included via the load profiles. Regarding the considered time horizon, the settings are evenly split up between considering only a single time slot and multiple time slots at once. Furthermore, unlike the previous cluster, settings covering only one time slot can not always easily be upgraded to multiple time slot models. This is mainly a consequence of the absence of one central model which can be split up into subproblems for each participant. Adapting all individual models while ensuring that the used techniques still converge to an equilibrium is more challenging. Regarding uncertainty, only some settings take that into account, even if a larger time horizon is modeled. Hence, no exact pattern between time horizon and uncertainty can be recognized, as there are settings with only one time slot, but also settings covering multiple time slots, which consider uncertainty. Due to the focus on individual objectives, techniques in this cluster have to be able to represent this selfish behavior, while ensuring that a stable solution is found. Game theory offers the right tools for such problems, and in most settings, a Stackelberg game is used to model the relation between the different participants. Other settings ignore the leader-follower dynamic of Stackelberg games and focus on general non-cooperative games. In some settings, either the non-cooperative or Stackelberg games are complemented by other techniques, such as auctions.

The first group consists of Stackelberg games in which prosumers are leaders and followers. The notion of the prosumer is generalized beyond the definition in Section 2.2, as companies that either buy or sell electricity are included. This setting is considered in [6, 67, 146, 161, 163, 203]. In [6, 146, 203], the set of prosumers is divided into a set of sellers and a set of buyers. The sellers act as the leaders in a multi-leader multi-follower Stackelberg game, while the buyers are the followers. The strategies of sellers and buyers can differ from one approach to the other. In [6] and in [146], the sellers start by announcing the amount of electricity they are willing to sell, and the buyers react with the prices they are able to pay. Based on these prices, the sellers update the amount of electricity and the game continues until convergence to a Stackelberg equilibrium. In [203], the strategies are quite different. The sellers announce their prices and the amount of electricity they are able to sell first, and then the buyers react with a selection of the sellers. This selection is a probability distribution for each buyer over the complete set of sellers and should indicate the probability of a buyer choosing a specific seller. The buyers compute this selection using an evolutionary game. Based on this selection, the sellers update their prices using a non-cooperative game. Note that hereby the amount of electricity to sell is a fixed parameter in this setting. Again, it is shown that the iterative Stackelberg game converges to a Stackelberg equilibrium. In [67, 161, 163] on the other hand, the prosumers are not in advance divided into buyers or sellers. In all these settings, the leader is a single entity that can buy and sell electricity and the followers are the set of prosumers. In [161] and in [163], the leader is a storage system within the microgrid, which can buy excess electricity or sell electricity to prosumers with a demand. Its goal is to maximize its profit, while the objectives of the prosumers are to maximize their own utility. The leader starts by announcing internal prices for the prosumers. Based on these prices, the prosumers can each solve their own (bounded) optimization problem to maximize their utility. They then announce their optimal amount of electricity to buy or sell, and the leader reacts to this by adjusting its prices. While the convergence of this iterative approach to a Stackelberg game is shown in [163], in [161] the model is based on a bi-level optimization problem, and no guarantees for convergence are made. In [67], instead of a storage system, a power company is the leader of the Stackelberg game. It first announces a price, based on which the prosumers play a non-cooperative game among themselves to determine how much electricity to buy or sell. Two different ways to achieve a Stackelberg game are proposed, with the first one being an iterative one leading to an ϵ-Stackelberg equilibrium, while in the second, the leader solves a non-linear optimization problem to directly find the Stackelberg equilibrium.

The second group of settings uses Stackelberg games to model the relation between the prosumers and their MGO or DSO. This setting is considered in [9, 10, 55, 142, 143, 162, 209, 253, 282]. In [55, 143, 162], the leader of the game is the MGO, while the prosumers are the followers. The goal of the leader is to maximize its profit and it starts by submitting initial internal buying and selling prices to the prosumers. The prosumers use these prices as input to their utility maximization problems and optimize them on their own. The prosumers then announce the amount of electricity to buy or sell and the leader updates its prices. The existence of a Stackelberg equilibrium is shown. In [9, 142, 253, 282], the leader is either a central power station, which wants to buy surplus electricity from the prosumers, the DSO, which wants to minimize the grid cost of the microgrid or retailers, who want to maximize their profit of selling electricity to the prosumers. The followers are once again the prosumers, who want to maximize their utility, or local MGOs, who want to maximize the social welfare of their set of prosumers. The leader announces initial prices or grid tariffs and based on this, the prosumers optimize their utility. In contrast to [55, 162], the prosumers either solve a generalized Nash equilibrium (GNE) game to decide how much to sell to the central power station, or they need to solve a complementary problem to compute an equilibrium. In both cases, the prosumers then announce their electricity consumption, either on an individual base, [253], or on an aggregated level [9]. Based on the reaction of the prosumers, the leader updates its prices and this iterative scheme continues until some convergence criterion is met. In [282] on the other hand, the bilevel problem is reformulated into a single-level MILP, which can easily be solved. A similar approach is taken in [10], where the trilevel problem is reformulated twice to obtain a tractable formulation. In the first step, an explicit formulation is derived for the prosumers, which removes the bottom layer. The remaining two layers, with the supplier being the leader and the MGOs being followers, are then reformulated using the Karush-Kuhn-Tucker (KKT) conditions of the followers in the leader's problem. In [209], the MGO also acts as the leader of the Stackelberg game, but instead of using price signals as a strategy, it uses demand profiles. In the beginning, the MGO collects the load profiles of all prosumers and optimally schedules its own battery usage. It then broadcasts the aggregated load profiles minus the prosumer's load profile to each prosumer. In addition, boundaries for the aggregated load profile and penalty prices are announced. The prosumers then optimize their utility function, which is a weighted sum of electricity costs, the comfort level, and the minimization of interruption to increase the life span of appliances. The prosumers announce their resulting load profiles to the MGO, which updates its battery schedule and possibly also the penalty prices. This process continues until the difference in the objective function of the MGO is reasonably small. It is shown that the iterative process converges to a Stackelberg equilibrium.

The third group of approaches uses general non-cooperative games to model the interactions between prosumers and other participants. The corresponding approaches are [57, 64, 86, 133, 145, 151, 223, 255, 273]. In [57, 86, 133, 145], a non-cooperative game is played among all prosumers. The utility functions of the players consist of the cost and the satisfaction of electricity consumption, while the strategies of the prosumers are their load profiles. In [86], the prosumer may be equipped with storage devices, and the market equilibrium problem is reformulated into a mixed complementarity problem using the KKT conditions. The resulting formulation is then solved via ADMM. A similar solution approach is presented in [57], where a non-cooperative game between prosumers, consumers, and generator units with possible failure times is modeled. The formulation results in a stochastic mixed complementarity problem, which solves the optimization problems of each prosumer and results in an equilibrium solution. In [133], a tailor-made billing scheme penalizes heavy electricity users, and it is shown that an iterative gradient-based algorithm converges to the NE of the game. In [145] on the other hand, the coupling constraints between the prosumers lead to a GNE. A detailed analysis provides insights into the efficiency of the GNE compared to a central solution. In [223], a GNE game is played between the DSO and the prosumers. The strategy of the prosumers is based on the amount of flexibility that they are willing to offer, while the strategy of the DSO is based on the fraction of the prosumers' flexibility that it wants to use, as well as a congestion price. Due to a coupling constraint between the prosumers as well as the DSO, a GNE is computed. In [255], a similar setting is considered, in which a power company is interested in buying surplus electricity from the prosumers, given a fixed budget. A cake-cutting game is proposed and a variational equilibrium is found using a decentralized algorithm. In [64], a non-cooperative game between a market operator, producers, and consumers is modeled. It is shown that a unique equilibrium always exists and a distributed algorithm is presented, in which producers and consumers react to the market operator's prices by adapting their production and consumption. In [273], two non-cooperative games between prosumers, the MGO, and suppliers are played. The MGO acts as a local aggregator between the prosumers on the one side and the suppliers on the other side. For the non-cooperative game between MGO and suppliers, the suppliers offer bids to the MGO. The MGO then uses these bids and the net demand of the prosumers to compute external trading prices with the suppliers. The utility function of the suppliers represents the profit they make by selling electricity to the MGO. The second non-cooperative game in [273] is played among the prosumers, who decide on their load profiles, given some predefined buying and selling prices for the given time interval. The utility functions of the prosumers consist of the cost of buying or the profit of selling electricity locally as well as the utility of electricity consumption. For both non-cooperative games, it is shown that a unique NE exists and an iterative algorithm is given, which converges to the NE. Both non-cooperative games are then connected via the MGO, which updates the external and internal prices after a change in either bids from the suppliers or the electricity consumption from the prosumers. In [151] on the other hand, a trilevel problem between the DSO, MGOs, and prosumers is modeled. Two different solution approaches, one cooperative and one non-cooperative are proposed. In both cases, the trilevel model is first reduced to a bilevel model by deriving an analytical solution to the non-cooperative game between MGOs and their respective prosumers. The remaining bilevel problem is then solved either in a cooperative or non-cooperative way using price and demand as signals.

The last group combines Stackelberg or general non-cooperative games with auctions [59, 103, 212, 251, 254, 263]. In the considered literature, there are two main ways to combine these approaches with each other. In [212] and in [263], a non-cooperative game is played among a set of prosumers with a surplus of electricity. The strategies of the sellers are specified by the amount of electricity they are willing to sell, while the utility is the profit they gain by selling electricity to the buyers. The prices are computed using a standard double auction between buyers and sellers, as is also often seen in the Strategic Matching without Flexibility cluster. After initializing the amounts to sell, the double auction is run, and based on the new clearing price, each prosumer one after the other finds best responses by communicating with the MGO, which acts as the auctioneer. It is shown that this iterative algorithm converges to a NE. In [103], a non-cooperative game is played among the prosumers of a microgrid. Each prosumer first solves a simple optimization problem to determine how much electricity to offer or ask for in the auction. Following a double auction, the winners participate in a non-cooperative game, in which each participant finds an optimal deviation from its original bid. This deviation maximizes a utility function, which consists of profit and the reluctance to deviate from the original bid. Afterward, the clearing price of the double auction is updated and the non-cooperative game continues, with each participant finding its best response to the new clearing price until a stopping criterion is met. Similarly to the above approaches, in [251], a modified version of a combinatorial auction is run. Within each iteration, players are added to the set of winners of the auction, based on the outcome of a non-cooperative game. In [59] and in [254] on the other hand, a double auction is run first to determine the set of winners of the auction, as well as the clearing price limits. Then, a Stackelberg game is played, with the MGO being the leader and the followers are either the winning buyers or sellers of the double auction. Using the range of possible clearing prices, the objective of the MGO is to maximize the average social welfare of the remaining set of winners. The strategy of the followers is to adapt the amount of electricity they are willing to sell or buy. This iterative process continues until the Stackelberg equilibrium is found.

3.3.4 Connections between Clusters

Based on the previous analysis of the clusters w.r.t. the used techniques and various aspects of the settings, we now identify and highlight connections between the three main clusters. Thereby, approaches from different clusters may complement each other when combined.

As already seen in the Equilibrium Balancing with Flexibility cluster, there are different approaches that combine the flexibility of this cluster with the auction-based approaches in the Matching without Flexibility cluster. This allows for an integration of a market-based pricing scheme into prosumers' decision processes and thereby extends the given approaches.

Another possible combination of approaches from two different clusters is to use the decentralized algorithms presented in the Joint Balancing with Flexibility cluster to compute an optimal solution, which can then be used in the Cooperative Pricing Scheme cluster. In both cases, the objective of the optimization problem is to minimize the sum of electricity costs of the microgrid. While the approaches in the Cooperative Pricing Scheme cluster are often based on centralized approaches along with their disadvantages regarding data privacy, decentralized optimization approaches (in the Joint Balancing with Flexibility cluster) could avoid this. In addition, new possibilities on how to fairly assign the benefits of cooperating among the participants may arise from this connection.

3.4 Conclusion

Summarizing, we can state that there are currently three main lines of research for local energy trading, each with a distinct setting and focus on one specific high-level research question of local energy trading:

1. The main goal of approaches within the Matching without Flexibility cluster is to match demand and supply, mostly by means of an auction. Prosumers can express their individual valuation in the form of bids and the MGO computes a clearing price, which maximizes the social welfare using well-established auction mechanisms.
2. The Communal Pricing Scheme focuses on creating pricing mechanisms that incentivize prosumers to be part of a microgrid. Instead of focusing on the load and flexibility of single prosumers, load profiles and flexibility of the whole community are combined to increase the overall profit. This additional profit is then split up between the prosumers, such that everyone profits from participation.
3. The last cluster is the Balancing with Flexibility cluster, which makes use of the flexibility of smart devices and the present loads to balance demand and supply. Using decentralized algorithms on the base of the underlying structure of the microgrid, the privacy of data can be ensured.

These central research questions within the clusters also align well with the considered research questions and findings of the analyzed literature. Combined with the different characteristics of the classification scheme, see Section 3.3, we can identify several future research directions and major open problems.

The first research direction, which has yet to gain focus in local energy trading, is the modeling of human behavior (see e.g. [204]). While it is reasonable (and necessary) to make some assumptions on prosumer behavior to analyze equilibria and their efficiencies, it has been shown that prosumers do not focus solely on the financial aspect of their decisions [171]. Based on the reviewed literature, two ways to integrate prosumer behavior into local energy trading can be identified:

1.1 A rather direct approach is to introduce different classifications of electricity, representing various aspects, such as 'green' or 'local' electricity.

Prosumers can then follow their individual preferences over these different types (see e.g., [182]).

1.2 Another approach is to extend the already existing utility functions of the prosumers by additional aspects, such as e.g. an ecological motive. Using game-theoretic approaches, a detailed analysis of equilibria w.r.t. differently weighted motives could reveal interesting results and insights for designing future energy policies and incentives.

The second research direction is the uncertainty in data. While it has already been considered in other related areas, such as power flow computations, this topic has not been studied much in a local energy trading setting. Most of the considered trading approaches simply use predictions or forecasts for the majority of their data. Although many publications across all clusters state the integration of uncertainty or stochasticity in data as an important, open research question, only a few approaches have already taken first steps to integrate uncertainty into their methods. We propose to start with the integration of robust or stochastic methods into approaches of the Joint Balancing with Flexibility cluster and then to further proceed with approaches in other clusters. This is based on the following reasons:

2.1 While the considered approaches mostly apply decentralized optimization techniques such as ADMM or C+I, these techniques are based on a centralized model of the setting or problem. For such a centralized model, it is often fairly straightforward to apply well-established methods, such as (adaptive) robust optimization or stochastic programming. The challenge then lies within the adaption of the decentralized optimization techniques to the updated formulations of the problem.

2.2 Most of the settings within the Joint Balancing with Flexibility cluster can cover time horizons of several hours and more. Within these time horizons, a considerable amount of uncertainty, compared to short time horizons of up to 15 min, can appear. Therefore, it is important to deal with the uncertainty in these settings first, before also considering smaller time horizons.

2.3 When applying techniques from robust optimization to the centralized models in the Joint Balancing with Flexibility cluster, additional synergy effects, due to uncertainty sets, may appear, when combining the robust approaches with the ideas of the Cooperative Pricing Scheme cluster.

It is worth mentioning that the integration of uncertainty has to be applied not only for local energy trading but also for energy management approaches, which are similar to the approaches in Joint Balancing with Flexibility.

The third future research direction, which up to now has not received much attention, is the integration of the physical infrastructure of microgrids into local energy trading. In large parts of the analyzed literature, the power aspect of the electricity grid is strictly separated from the energy aspect of local trading.

Future work in local energy trading has to integrate the power aspect into the approaches to ensure a stable electricity distribution. There are two main ways how to achieve this:

3.1 The direct approach integrates the power aspect by means of constraints, directly modeling the power flow and grid constraints. Approaches in the Joint Balancing with Flexibility cluster are once again a good starting point due to their central optimization models, in which different versions of power flow approximations can easily be integrated.

3.2 The indirect approach makes use of different steering approaches, such as e.g., congestion prices. These can then encourage or discourage prosumers to consume more electricity or curtail their PV generation. Approaches within the Matching without Flexibility clusters are a good starting point to integrate the power aspect in an indirect way (see e.g., [128, 262]).

4 Human behavior: Modeling prosumer preferences for a local electricity market

Abstract – *In this chapter, the first aspect identified in Chapter 3, namely the modeling and analysis of human behavior in local energy trading, is followed upon. The focus lies on the impact of human behavior and preferences on the outcome of local electricity markets (LEMs). Within the last few years, LEMs have significantly gained attention, but there is still a gap in the knowledge of the impact and influence of human behavior on the outcome of LEMs. Motivated by this, human behavior and preferences are modeled and integrated into a home energy management system (HEMS), bridging the gap between end-participants and the LEM. A behavioral model from social sciences is used to explain the interactions between internal motives and preferences, and is translated into a multi-objective optimization model. Based on this, human preferences and behavior are modeled as several input or device parameters for the HEMS and their impact on the outcome of the bidcurves of an individual household is analyzed. In a second step, the focus shifts onto the impact of the parameter choices on the outcome of a LEM.*

4.1 Introduction

One of the main conclusions of Chapter 3 is that in the current state of research on local energy trading approaches, the aspect of human behavior has rarely been considered. Within this chapter, we focus on local electricity markets (LEM), which are seen as a promising approach to enable local energy trading for households. In LEMs, small-scale end users, such as households, can directly trade

This chapter is based on [JH:2].

with each other or the electricity market (see e.g., [61, 118]), and are therefore an extension of classical electricity markets, as introduced in Chapter 2.

It is obvious that human decisions affect the usage of local devices, such as EVs or PVs, via charging and usage preferences [JH:8]. As LEMs enable individual households to participate and submit their own bids [183], human preferences, behavior, and decisions will also be a part of the bids and thereby of the LEMs. Therefore, human behavior should be considered when designing or analyzing LEMs. However, the current research on energy trading and LEMs focuses either on optimal bidding strategies for individuals [156, 272] or on market frameworks for flexibility services [138]. Bidding research often uses game-theoretic tools to analyze the impact of individual bids on markets and to derive optimal strategies, as seen in Section 3.3. However, these approaches often rely on very simplistic settings, considering only one type of device or flexibility, and therefore do not fit well for future scenarios, where households will have multiple devices and sources of flexibility. Market-oriented research on LEMs, on the other hand, focuses less on individual bids, and therefore often overlooks the impact of human preferences within the market design [61].

Within the area of energy management systems (EMS), on the other hand, the idea of using multiple objectives, potentially representing different human preferences, has already been proposed [210, 224, 265]. While most of these approaches focus on a microgrid level and include objectives, that may not be of interest to individual households, such as voltage constraints [210, 224], some of the literature already connects the different objectives of a multi-objective energy management system to human behavior and preferences [265]. This modeling on a household level allows the prosumer to integrate their individual preferences into the EMS. What is still missing in current research is the link to LEMs and the impact of these different preferences on the performance and outcome of such a LEM.

Hence, a research gap exists in understanding the influence of human preferences on the effectiveness of LEMs. Currently, limited attention has been given to incorporating multiple device types and considering the impact of human preferences on bidding strategies and market design. Further research is needed to bridge this gap by integrating human preferences, considering the complexities of future scenarios with multiple devices, and exploring the role of home energy management systems (HEMS) in creating bidding strategies and their impact on the overall performance of LEMs. This chapter tries to contribute to this gap by modeling a HEMS, which takes human preferences and behavior as input parameters and creates tailor-made bidcurves for participation in a LEM. We investigate different human behavioral models from social science and focus on the Attitude-Behavior-Context (ABC) model [87]. We then translate the behavioral model into a mathematical multi-objective optimization model, which serves as the core of the HEMS. The case study can be split into two parts. In a first step, we investigate the impact of human behavior and preference on the bidcurve of an individual household. We thereby connect the results of this case study to the description of the ABC model. In a second step, we carry out a sensitivity analysis on the parameter choices of multiple households and their impact on the outcome of a LEM. The results emphasize the need to properly align the steering signals of LEMs with the participants' goals to ensure proper working of the market.

The chapter is structured as follows: Section 4.2 explores human preferences and behavioral models and the method used. The LEM is presented in Section 4.3. In Section 4.4, the household bidding model is introduced. The results are presented and analyzed in Section 4.5. We summarize the results and discuss our work in Section 4.6.

4.2 Behavioral models

In this section, we provide a short introduction to the topic of human behavior in social sciences. We present and compare three different behavioral models, and then apply one of them to the case of creating bidcurves for a local electricity market.

Turning off the lights, lowering the temperature settings, or charging the battery is not directly human behavior but is the consequence or result of human behavior. Within the area of energy-related topics, human behavior has already been studied and researched for many decades [19, 115].

Most of the work on this topic has focused on changes in human behavior in energy consumption and savings [115, 171]. While many of these results are still valid, the situation in which households must make decisions has changed considerably within the last few years and will continue to change drastically within the coming years [90]. LEMs give individual households direct access to electricity markets, and devices, such as PVs, batteries, or HPs, provide flexibility for the energy profile of households.

This study focuses on the consequences of human behavior and preferences on the considered devices and their effect on the LEM. Other decisions, such as turning off the lights, or long-term investments, such as improving the insulation of houses, are not considered. In the following, we present three well-established behavioral models or theories, which have already been applied to behavioral modeling and analysis in the context of energy usage. It should be noted that other behavioral models may also be applicable to the considered setting.

4.2.1 Rational Choice Theory

A well-known and widely adapted theory in economics is the Rational Choice Theory (RCT). At its core, it assumes that consumers choose the action that best helps them achieve their goals, given external information and factors, that are beyond their control [85]. The main assumptions of RCT are that consumers know all of their possible actions, there exists a complete and transitive preference system over the set of actions, and the consumer will choose the most preferred action. In most case studies, the preference system is modeled as a utility function, which maps each action to a numerical value. Choosing the most preferred action then translates to the problem of solving a (constrained) optimization problem over the utility function [85]. Due to its often simple assumptions, RCT has successfully been applied to a variety of research fields, starting from economics to problems in sociology, political science, or pro-environmental behavior (PEB) [85, 115, 171, 248, 252]. However, RCT is often also criticized for its simple assumptions. The main disadvantage is the focus on external factors, as well as the assumption of a transitive preference system, which in practice may not always be the case. In [104], the basic model, as described above is referred to as a 'thin' model, while the 'thick' model does include intrinsic motives, such as values and beliefs of the consumers. However, these thick models often go beyond the main assumptions, and can therefore be seen as a new branch or family of behavioral models.

4.2.2 Value Belief Norm Theory

One theory, which is explicitly built upon intrinsic motives is Sterns' Value Belief Norm Theory (VBNT) [236]. It combines three existing theories, namely the value theory [218], the new environmental paradigm [63] and the norm-activation model [217] and creates a clausal chain between those theories [236, 248]. VBNT is developed to explain PEB, which often requires limiting selfish behavior and tendencies in favor of communal or societal objectives and goals [199, 252]. It assumes that internal values, such as being altruistic, egoistic, or traditional, influence the beliefs of individuals. In a PEB context, these beliefs form a chain, where an ecological worldview leads to the awareness of consequences, which in turn leads to a sense of responsibility. These beliefs then form the pro-environmental norms, which directly lead to behavior and actions. VBNT has successfully been applied to various problems in the context of PEB, such as urban transportation choices [157], or the development of urban parks [166]. It has also been used to explain behavior in the context of solar energy usage [11], energy conservation [110] or the acceptance of energy policies [233]. One central conclusion found in [233] is that although VBNT can be used to explain behavior to a large extent, the explanatory power diminishes in the presence of strong external factors, such as monetary incentives. Therefore, VBNT may not be best suited to model behavior in the context of a LEM, in which monetary incentives play a central role.

4.2.3 Attitude-Behavior-Context Model

A model that combines both internal and external factors is the ABC model [87]. The core idea behind this model is that 'behavior (B) is an interactive product of personal sphere attitudinal variables (A) and contextual factors (C)' ([235],

p. 415). The ABC model thereby closes the gaps between RCT and VBNT by including both internal variables and external factors. These factors and variables can be described as follows:

» *Attitude*: These are the internal, intrinsic variables and factors, such as norms, motives, (inner) beliefs, or values.

» *Behavior*: Within this model, the behavior can be observed via decisions or outcomes.

» *Context*: The context contains the external factors influencing the behavior. Among these are monetary incentives such as costs or profit, access to technology or devices, social norms in the form of peer pressure, regulatory frameworks, and laws.

In addition, the ABC model not only includes both types of factors individually but also explains how these factors may interact with each other. It claims that the influence of attitude on behavior is strongest when the context is neutral, which is in line with the observations in [233] and that a strong context leaves little room for the attitude. Stern also provides evidence for this claim in the form of a research project on recycling, see [87]. The ABC model has successfully been applied in behavior research, mainly in PEB analysis such as organic food consumption [214], recycling behavior [87, 195] or energy savings or usage [7, 74, 109, 266].

4.2.4 Application to a Local Electricity Market

Based on this brief overview of well-established behavioral models, we proceed with an application of one behavioral model to the setting of modeling bidcurves, subject to the influence of human behavior. As the main principles of the ABC model fit well into the setting of a LEM that is affected by human behavior, we now set up the model in the context of creating individual bidcurves for a LEM. This allows us to model human preferences (attitude) and access to devices (context), influencing the bidcurve (behavior). The general attitudinal, behavioral, and contextual factors and variables in this context are defined as follows:

» *Attitude*: Three main internal variables in the form of motives are introduced. The first one is an *ecological motive*, in which households prefer to use electricity from fossil-fuel-free energy generation, such as PV or wind power. The second motive is the *comfort motive*, which tries to minimize temperature deviations from the desired set point and charge the EV as fast as possible. The last motive is the *financial motive*, which aims to maximize the profit gained from buying and selling electricity at different time slots. Both ecological and financial motives have been used extensively throughout behavior research in energy savings [228, 229], and are, therefore, included in this study. The comfort motive has yet to see much attention in electricity savings or management, which can partially be attributed to the past's lack of electric heating and mobility opportunities. However, this will likely change soon with the increase of EVs and HPs [113, 114]. In addition, early behavior research on energy savings [19], already analyzed the importance of house temperature as an indicator of energy savings. Furthermore, EV range anxiety makes people want to charge when the state-of-charge (SoC) is lower [205]. Therefore, we integrate these factors into this study by including the house temperature and the EV SoC as factors for the comfort motive. The remaining devices in the form of PV and batteries, on the other hand, do not affect the comfort. Apart from these devices, comfort is also affected by the household load. This load is, however, assumed to be non-steerable.

In addition to these motives, different household preferences that may affect the operation of devices are also considered. These preferences are a temperature range in which the house temperature should be and a desired SoC for the EV. Note that setting an individual temperature range also limits the loss of comfort, which has been shown to reduce prosumers' willingness to participate in energy management approaches [56].

» *Behavior*: In this setting, the bid of a household represents the behavior. It is influenced by both internal motives, as well as the access to devices within the household.

» *Context*: This study focuses on a future scenario where households can access various devices. These devices are PV systems, batteries, EVs, and HPs, as these are among the most common devices in LEM literature [60]. Apart from these devices, we consider electricity prices, CO_2 emissions, and grid constraints as external factors.

Additional behavioral aspects, such as peer pressure within a neighborhood are deliberately not modeled, due to two main reasons:

» Peer pressure could encourage or discourage households from gaining access to devices, such as an EV or HP. However, this access to devices is a long-term investment, which we do not consider within the scope of this setting.

» Next to the access to devices, peer pressure can also have an influence on the internal motives of households. However, we do not claim to know the exact distribution of individual motive weights, and can therefore assume that peer pressure, as well as internal values, beliefs, and morals, have together formed the motive weights as used within our formulation.

This general list of internal and external factors and variables must be adjusted for every household to make up for personal preferences and conditions. Regarding the three different motives, households may have different preferences and do not simply follow a single motive. Hence, we introduce the (individual) motive

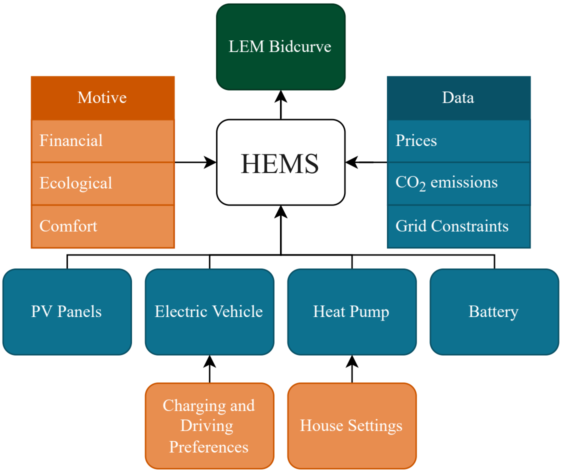


Figure 4.1: Overview of the applied Attitude-Behavior-Context model, with the attitudinal variables in orange, the contextual factors in blue, and the behavioral outcome in dark green; the household preferences and distributed energy resources at the bottom provide flexibility, while the motives and other data inputs define the preferred usage of flexibility.

weights w_e, w_c, and w_f corresponding to the ecological, comfort, and financial motives and representing the individual preferences of each household over these motives. W.l.o.g., we assume that $w_e + w_c + w_f = 1$ and $w_e, w_c, w_f \geq 0$. These weights can, therefore, be seen as percentages of the corresponding motives on the overall attitude of each household. Note that even though these motive weights may change over time, we assume them to be fixed.

Figure 4.1 depicts the ABC model applied to the process of creating a bid for an individual household. The HEMS, connecting all aspects, corresponds to the automated implementation of the ABC model, which is explained in Section 4.4. Note that the households can control all of the attitude variables, apart from the driving decisions. These driving decisions are assumed to be fixed and already included in the EV data. All of the contextual factors are also fixed and cannot be controlled directly by the households.

4.3 Market and Energy Provider

4.3.1 Local Electricity Market

Due to the scoping of this study, the LEM needs to allow humans to set parameters in a HEMS influencing the bidcurve, meaning that the HEMS creates a bidcurve based on parameter values and constraints set by the households. Therefore, the LEM chosen for this study is similar to the LEM in [62] and focuses on the low-voltage sections of the distribution grid, enabling small-scale participants, such as individual households, to submit bids and thereby directly participate in the energy market. The LEM allows participants to bid directly into the LEM, but an aggregator purchases electricity for the neighborhood day ahead on the wholesale market to ensure sufficient market liquidity. Therefore, direct participation takes place under the umbrella of an aggregator.

The considered LEM is based on a double-sided auction and operates in an intraday fashion, meaning that it works with 15-minute time slots and its price-forming mechanism takes place before the start of each time slot. It should be noted that the LEM focuses on electricity procurement rather than flexibility. However, the HEMS identifies and uses the flexibility of the devices to optimize for the preferred objectives of the household. For each market iteration, there are two bidcurves in a double-sided auction. In this study, the demand bidcurve of the households represents the possible buying decisions and actions of the household, whereas a negative value of the bidcurve implies the intention of selling electricity. The energy providers submit supply bidcurves, in which a positive value represents selling electricity to the households, while a negative value represents the action of buying electricity. Figure 4.2 displays an example of two such bidcurves. It should be noted that each bidcurve consists of pairs of price and the corresponding energy.

The market mechanism works as follows: After receiving the bidcurves from the households and the energy providers, the household bidcurves are first aggregated. The same happens for the bidcurves of the energy providers. Next, the crossing point of the two aggregated bidcurves is determined. This point then defines the initial clearing price and the corresponding energy volume. If the volume of cleared energy is within the grid constraints, the clearing price is communicated to the participants, who then act according to their submitted bidcurves. Otherwise, if the initial clearing volume exceeds the grid constraints by consuming or producing too much power, the clearing price is adjusted to the corresponding volume within the grid limits. This procedure is introduced and explained in detail in [134]. Any imbalance between demand and supply caused by this approach is then assumed to be handled by predetermined agreements between the aggregator and balancing responsible parties, which are not part of this study.

4.3.2 Energy Providers

In this study, the focus is on modeling human preferences in households and, therefore, we do not consider the effect of human preferences on the bidcurves of the energy providers. The LEM presented in the previous subsection allows for multiple energy suppliers or providers to provide a bid. This could involve energy suppliers and various local PV plants, wind turbines, or other entities in a real-world scenario. However, in this study, a limited number of fifty households is considered requiring a more controlled approach. Therefore, we ensure that whatever the household bids, there is always a match between the bidcurves.

The bidcurve of the energy providers for a fixed time slot t_0 consists of three parts. The first part corresponds to the purchases of an energy supplier at the clearing price of the wholesale day-ahead market. The amount the aggregator buys or sells is decided based on a prediction of the energy demand of all households. This prediction is based on the household loads, the PV generation, as well as the demand for the HPs and EVs:

$$\sum_{h \in house} \left(p_{t_0}^{h} - p_{t_0}^{PV,h} + g^{HP}(h, t_o) \right) + c^{EV}(t_0) \cdot \bar{p}^{EV}, \tag{4.1}$$

In equation (4.1), $c^{EV}(t_0)$ represents the expected share of EVs connected to the grid at time slot t_0, while $\bar{p}^{EV}$ corresponds to the average EV demand based on historical data. $g^{HP}(h, t_o)$ estimates the required power to keep the desired house temperature of house h given the outside temperatures at time slot t_0. $p_{t_0}^{h}$ and $p_{t_0}^{PV,h}$ correspond to the estimated household demand, respectively PV generation of household h during time slot t_0. To account for the bids of the remaining energy providers, we reduce this predicted demand of the set of households by a factor α, $0 < \alpha < 1$. In this study, the other energy providers are a wind power farm and a provider of short-term flexibility.

The second part of the bidcurve represents a surplus of wind generation compared to the expected wind generation. This surplus may be sold at the local intraday market, represented by the LEM. Given the intermittent nature of wind generation, the inclusion of wind power leads to higher fluctuations in the aggregated bidcurve of the providers over time. The amount of energy is a percentage of the purchased energy from the aggregator to ensure a match between the bidcurves. This percentage depends on the national wind production in the Netherlands [120] and is chosen in such a way that the overall energy at the market is in the same order of magnitude as the (aggregated) bidcurve of the households, but differences may occur.

To ensure that in this limited market setup, an intersection always exists between the bidcurves of the households and the energy provider, we introduce an additional energy provider, offering expensive, short-term flexibility. We assume that this energy provider can sell and buy sufficient energy from the LEM, thereby ensuring that the two bidcurves intersect.

4.4 Mathematical Model

In this section, we introduce a bidding model for an individual household based on the ABC model whose output fits the input of the previously presented LEM. We first provide the general framework for computing the bidcurve and then present insights into the details of the mathematical formulation, in particular of the objective function.

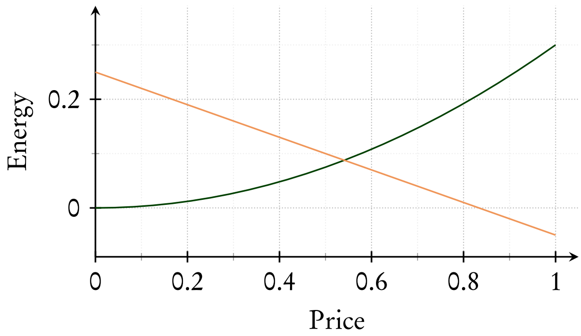


Figure 4.2: Sketch of the clearing procedure of a household bidcurve (orange) and bidcurve of the energy providers (dark green).

4.4.1 Framework

Given the presented LEM, each household must submit a bidcurve to participate in the clearing of the LEM, which occurs at the beginning of each time slot. Each bidcurve submitted to the LEM consists of a set of price-volume pairs. To reduce the computational burden, we choose a fixed number N of price points, equally distributed within the given price range, and compute the optimal buying and selling decisions for each given price point individually. Based on this, we linearly interpolate the solution between the price points and thereby construct a piecewise linear bidcurve, which can then be submitted to the LEM. Algorithm 1 displays the scheme for approximating the individual bidcurve for a given household for time slot t_0.

» *BidCurve* is a vector used to store the buying and selling decisions for each price point.

» *PriceSteps* represents the given choice of price points within the price range. These price points are the same for each household and energy provider.

» *localHEMS* is the local decision problem of finding optimal buying and selling decisions for a price point *PriceSteps*$[i]$, a time horizon $[t_0, t_0 + Hz]$ with $Hz \in \mathbb{N}_{>0}$, as well as the house-dependent *Data*, such as the individual motive weights, the device parameters, or further information, such as prices or weather data.

Based on this framework to compute the bidcurve for a single house, the decision problem of finding optimal buying and selling decisions (*localHEMS* in Algorithm 1) is specified in more detail. In general, we slightly adapt the mathematical formulation presented in Chapter 2 to represent the decision problem for an individual household. Within this model, the operating limits of the devices are represented by constraints, while the different motives build up the objective function.

Algorithm 1: Bidcurve model for time slot t_0 for a single household

BidCurve $\leftarrow [0, 0, ..., 0, 0]$ of length N;
initialize *PriceSteps* (equal for each household);
for $i \in [1, .., N]$ **do**
  solve *localHEMS*(t_0, t_0+*Hz*,*PriceSteps*[i],*Data*);
  BidCurve[i] $\leftarrow (x_{t_0}^{buy} - x_{t_0}^{sell})$ is the market interaction given price *PriceSteps*[i];
  save PV, battery, EV, and HP usage;
Interpolate *BidCurve*;
Result: *BidCurve* and other saved data points

4.4.2 Variables and Constraints

As already mentioned, the underlying optimization model is mainly based on the same variables and constraints as presented in Chapter 2. W.l.o.g., let $\mathcal{T}'$ denote the considered time horizon $[t_0, t_0 + Hz]$. The device variables and constraints for the PV system, the battery, the EV, and the HP are constructed exactly as presented in Section 2.3 for the time horizon $\mathcal{T}'$. The demand-supply-balance constraint (2.15) is then constructed only over the considered devices of the individual household, including its household load. The only large difference on the constraint level can be found in the market exchange variables and constraints. Instead of modeling the day-ahead and the intraday market, we only consider a single market, namely the LEM, in which the household participates. Note that the demand-supply-balance constraint therefore only considers a single market.

Due to the linear constraints, the resulting set of feasible solutions is a convex polyhedron. This implies that the convex combination of any two feasible solutions lies within the polyhedron and is, therefore, feasible again. Hence, we can interpolate any two feasible solutions and again receive a feasible solution. This is a necessary property to be able to implement Algorithm 1, which creates the bidcurve by interpolating neighboring price points.

4.4.3 Objective Function

The objective function is the most interesting aspect of this optimization model, as it represents the concept of motives and preferences, which drive human behavior. As explained in Section 4.2.4, households usually do not follow only a single motive, but a mixture of different motives. To represent this motive mixture, we have introduced the motive weights w_e, w_c, and w_f for the ecological, comfort, and financial motives. Similar to the well-known concept of a weighted sum of objectives from multi-objective optimization, we use these motive weights to create one objective function as the weighted combination of the three motives. In the following, we first formulate each motive as an individual objective function before combining them into a single final objective function.

Ecological Motive:

The goal of the ecological motive is to reduce the CO_2 emissions of the consumed electricity, leading to the following objective function:

$$\min OF_e = \sum_{t \in \mathcal{T}'} \lambda_t x_t^{buy}, \tag{4.2}$$

where λ_t is a forecast of the average grid emission factor, [177], which is applied to the bought electricity at the LEM.

Comfort Motive:

Within this thesis, we define comfort as being related to the house temperature as well as the SoC of the EV. Hence, maximizing comfort relates to minimizing the deviations in temperature from a pre-defined preferred temperature, as well as to maximizing the SoC of the EV:

$$\min OF_c = \sum_{t \in \mathcal{T}'} (t_{t,1}^{HP,house} - t_t^{house,set})^2 - \eta SoC_t^{EV}, \tag{4.3}$$

where $t_t^{house,set}$ denotes the preferred house temperature for time slot t, and SoC_t^{EV} denotes the SoC of the EV at the end of time slot t. Note that SoC_t^{EV} can be computed by dividing the energy balance of constraint (2.5) by its capacity C^{EV}. The additional factor $\eta \geq 0$ represents the individual balance between the two components of the objective function.

Financial Motive:

The financial motive aims to decrease the costs and increase the profit of participating in the LEM. Hence, the objective function is based on the buying and selling decisions:

$$\min OF_f = \sum_{t \in \mathcal{T}'} \pi_t^{buy} x_t^{buy} - \pi_t^{sell} x_t^{sell}. \tag{4.4}$$

The main challenge with the financial objective is that it depends on the future clearing prices π_t of the LEM, which are not known yet and which can be seen as a highly correlated, stochastic process. Hence, the decision problem of submitting a bidcurve is a highly complex problem, which depends on future, uncertain demands and supplies of households and energy providers. However, the LEM operates in an iterative fashion, in which only the bidcurve for the current time slot t_0 is required. Therefore, we restrict the price dynamics to the current time slot. For future prices, we use predictions of the clearing price of the LEM, which, in this case, are based on the day-ahead market clearing prices.

These prices are slightly adapted to reflect the decisions of the supplier side by assuming a small increase in price for buying decisions and a small decrease for selling decisions. The price dynamic for time slot t_0 is based on the price range *PriceSteps*, as introduced in Algorithm 1. This choice of modeling the prices is an approximation of the underlying stochastic pricing process. However, due to the limited impact of a single household bidcurve on the clearing process of the LEM, as well as the increasing uncertainty for future demand and supply, this decomposition of the pricing process still holds approximately.

The individual motive weights are used to combine the three objective functions. However, similar to the *linear scalarization* method from multi-objective optimization [66], we first normalize each objective function (4.2)-(4.4) to the interval $[0, 1]$ by analytically deriving upper and lower bounds on each objective function. This normalization process ensures that the weights actually represent the intended preferences and that no single motive dominates the others due to a large objective value, even if its motive weight may be small. Let OF'_e, OF'_c, and OF'_f represent the normalized versions of the objective functions. Then the final objective function is:

$$\min w_e OF'_e + w_c OF'_c + w_f OF'_f. \tag{4.5}$$

Combing the constraints presented in Chapter 2, describing the set of feasible solutions, with the objective function (4.5), gives the optimization problem for the current time slot t_0 for a single household to decide how much to buy or sell based on the given price *PriceSteps*$[i]$. This procedure now repeats for each price in *PriceSteps*, before the bidcurve for the household can be interpolated. Algorithm 1 can now be applied to each household, and the resulting bidcurves can be added up for the final bidcurve for the LEM.

4.5 Analysis

Within the following, we analyze the impact and effect of the motives behind human behavior on various aspects of a LEM using the introduced bidding model and LEM. We first introduce the simulation setting, including the considered data, time horizon, and motive weights. The following analysis is split into three parts. In a first step, we focus on the bidcurves of an individual household and analyze the impact of the motives and the device setting on the bidcurves. We then compare the results to the claims of the ABC model. The second part analyzes the bidcurves from a multi-objective point of view. We only focus on the motive weight and assume a fixed setting in which the household has access to all devices. The third part includes the LEM and analyzes the effect of specific motive mixtures on the outcome of the LEM. We compare the results w.r.t. different grid metrics, as well as the three individual objectives.

4.5.1 Simulation

Data: All test scenarios include a LEM with fifty households, each equipped with PV, an EV, a battery, and an HP. The household and PV data is taken from [62], and the household load is based on the yearly average Dutch household load profile and scaled to match an average yearly consumption of 3250 kWh. The PV generation is created by combining solar irradiance data with the expected yearly PV generation, corrected for roof area and angles of the Dutch city of Arnhem.

The EV data is taken from [JH:7], where EVs have a 50 or 75 kWh battery and a home charger of 11 kW. The driving decisions and EV demand are included in the data and assumed to be known to the household. The battery is modeled after a Tesla wall-mounted battery with a capacity of 13.5 kWh and charging and discharging limits of 5 kW. The HP is a simplified version of the HP model presented in [261], whereby differences are the lack of a minimum operating limit and the omission of a minimum downtime requirement. In addition, the demand for domestic hot water is not considered. However, the possibility of cooling the house during summer is added.

The wind data used as input for the bidding model of the energy provider comes from [120]. The day-ahead prices used for the LEM and the financial motive are from the Dutch wholesale market in the year 2020, and the average CO_2 emissions are based on the energy contribution per production type in the Netherlands during the year 2020 [72, 73]. The price range considered in the LEM ranges from the day-ahead price in kWh minus 0.03 €/kWh to the day-ahead price plus 0.07 €/kWh to align with the purchase of the energy supplier. The household grid limit is 3×25 A or 17.25 kW to allow the households to use the DERs simultaneously. The grid limit where LEM intervenes and adjusts the bidcurves is 141 kW.

Horizon: The time horizon for the optimization model and data availability is set at four hours or sixteen time slots. In a sensitivity analysis, this duration was found to be a good balance between results, future knowledge, and simulation duration. The data for these four hours available to the HEMS is the outside temperature, EV arrival and leave times and energy requirements within this four-hour window, future PV generation, wholesale day-ahead prices for the financial motive, and emission factors for the ecological motive. In this window, HEMSs cannot access LEM data such as wind generation and clearing prices.

Number of price points: The influence of the number of price points N on the bidcurves, and thereby on the clearing of the LEM, is mainly based on the distance between the price points. Given the used price range around the day-ahead price of 0.1 €, we choose $N = 20$, resulting in a distance of 0.00526 € between two consecutive price points. Therefore, the clearing price is at most 0.00263 € away from the nearest price point and thereby from an optimal solution. We deem this difference to be small enough in a real-world implementation to assume that the difference between an optimal solution at the clearing price and the submitted bid is negligible.

4.5.2 ABC Model Validation

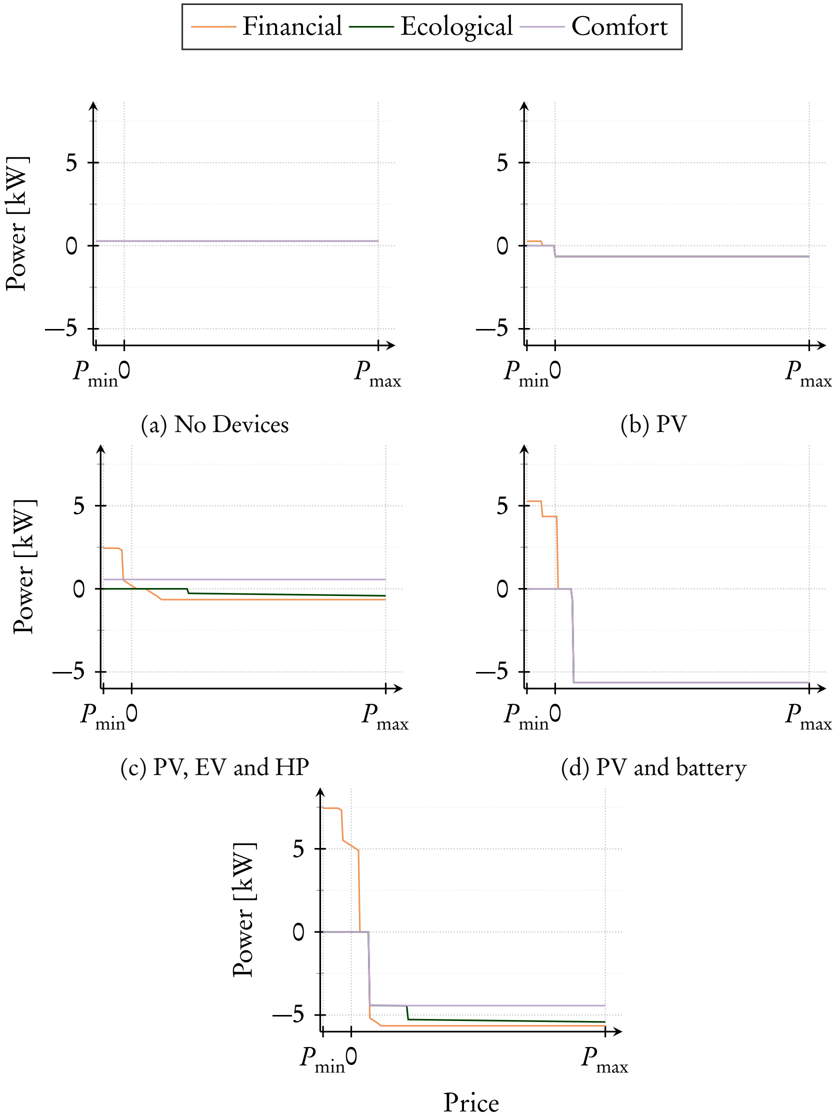
In this section, we verify whether the characteristics of the ABC model can also be observed within the context of a bidcurve for a LEM. One of the core aspects of the ABC model is its explanation of how the influence of attitude on behavior changes depending on the given context [87]. It claims that the influence of the attitude is strongest when the context is neutral and that an extreme context leaves little room for the attitude, see Section 4.2.3.

One large difference of the ABC model in most case studies is that the explained behavior is the willingness to follow some PEB actions, such as recycling [87] or saving energy [266]. The behavior part in our application of the ABC model however corresponds to the bidcurve of a household, which has to be submitted to the LEM, independent of the attitude or the context. This poses a large difference to the simple decisions of whether (and how much) to recycle trash or to save energy (which can easily be measured). Hence, instead of being able to directly measure the outcome of the behavior, we need to closely evaluate and compare the bidcurves to decide or quantify the impact of the context on the attitude.

In general, the attitudes aim at different aspects of the bidcurve. The financial motive tries to adjust the whole bidcurve to increase the profit of participating in the LEM. The ecological motive on the other hand tries to minimize the CO_2 emissions of the bought electricity. Thereby, it mainly tries to reduce buying electricity from the markets, but has no preference on selling electricity at the LEM. Finally, the comfort motive only cares about the usage of the EV and the HP. In the following, we investigate whether these differences in the goals of the attitudes can also be observed depending on the context.

Results

Figure 4.3 displays the bidcurve of an individual household for various device settings and motive mixtures for a sunny morning. The device settings range from no devices (Figure 4.3a) to all the considered devices (Figure 4.3e). In this analysis, EV and HP are only considered together, as both contribute to the comfort motive and also offer the same type of flexibility, namely a possible delay in charging. Note that for the chosen time slot the EV is available and the PV system is generating electricity. The three presented motive mixtures represent extreme weight choices, namely 0.98 for the naming motive and 0.01 for each of the remaining motives.



(e) PV, EV, HP and battery

Figure 4.3: Bidcurve for an individual household for a sunny morning for three motive mixtures and five device configurations.

Analysis

Comparing the bidcurves in Figure 4.3 with each other, we directly notice that the considered devices have a significant impact on the bidcurves.

Starting with the case of no or only few devices (see Figure 4.3a and 4.3b), we observe that the different motives still lead to nearly identical bidcurves with only minor differences. This can be explained by the lack of flexibility, which does not allow for a large variation of bidcurves.

Adding an EV and an HP leads to a scenario, in which the bidcurves of the various motives start to deviate from each other (see Figure 4.3c). While the comfort motive results in a perfectly flat line as the bidcurve, the financial motive makes use of the possibility of additional charging (of EV and HP) to increase its profit for negative prices. For positive prices, on the other hand, it falls back to the strategy of selling its PV surplus, as already observed in Figure 4.3b. The ecological motive also first prioritizes its main goal, namely avoiding buying electricity from the LEM. However, beyond this decision, there is a trade-off between the two remaining minor motives. While the comfort motive would use the remaining PV surplus to charge EV and HP independent of the price, the financial motive would sell the surplus given a positive price. As the profit of the financial motives increases linearly with the price, the decision of what to do with the remaining PV surplus gradually shifts from the comfort motive to the financial motive (see the ecological bidcurve in Figure 4.3c).

Adding further flexibility in the form of a battery leads to a scenario in which the bidcurves of the different motives share more similarities again (see Figure 4.3d and 4.3e). Independent of the motive, there is a common price point, where each bidcurve experiences a sharp drop. Although the levels before and after this price point may differ between the motives, the overall shape is nearly identical. One important observation is that the battery offers so much additional flexibility that the ecological and comfort motives can easily reach their primary goals, and use the remaining flexibility to also align with their secondary objectives. This then leads to the similarity in the shape of the bidcurves. The financial motive on the other hand can increase its profit with every additional kWh it can buy or sell (depending on the price), and therefore makes use of the whole battery flexibility.

Summarizing the above analysis, we observe that the influence of the motives on the bidcurve is strongest when the device flexibility is not too small or too large. In case of very little flexibility, the motives do not have a large impact on the bidcurves, while a scenario with plenty of flexibility also results in very similar bidcurves. This aligns well with the claim of the ABC model ([87]) and strengthens our choice of using the ABC model to analyze the impact of human behavior and decisions on a LEM.

4.5.3 Multi-Objective Analysis

In the previous section, we analyzed the bidcurves from the perspective of the ABC model, however, we did not pay attention to how the bidcurves evaluate w.r.t. the objective functions. Therefore, in this section, we use a multi-objective perspective to analyze the bidcurves of an individual household. In contrast to classical multi-objective optimization, evaluating a bidcurve does not lead to a simple set of objective values, but to a set of functions, each representing an objective function. Hence, plotting the various solutions against each other, as usually done to identify the pareto front, cannot easily be done. Therefore, we restrict the plots to individual plots of each objective function against the price dimension of the bidcurve. Hereby, we focus on the motive mixtures already used in Section 4.5.2 and consider all devices.

Results

Figure 4.4 displays the bidcurves for the three extreme motive mixtures and the full device setting (see Figure 4.3e) evaluated w.r.t. the four objectives. Note that for Figures 4.4a - 4.4d only the current time slot is evaluated, while Figures 4.4e and 4.4f show the results for the financial and ecological objective evaluated for the whole considered time horizon. Both financial and ecological objectives want to minimize the cost, respectively the associated CO_2 emissions, while the EV part of the comfort objective aims to maximize the SoC of the EV. The temperature aspect of the comfort objective wants to minimize the (squared) deviation from the preferred temperature set point. In Figure 4.4b, we show the temperature deviation to also know whether the deviation is positive or negative.

Analysis

Analyzing the different objectives of the bidcurves for the current time slot in detail, we first notice that the financial motive mixture is not always the best w.r.t. the financial objective (see Figure 4.4c). For a very small price range, the costs are larger than for the bidcurves of the ecological and comfort motives. This can be explained by the objective function of the model and the way how the bidcurves are evaluated. Within the optimization model, as presented in Section 4.4, the objective function spans not only the current time slot but also covers (some) future time slots to account for future prices, demand, and generation, see Section 4.5.1. If, however, we evaluate the same bidcurves for the whole considered time horizon (see Figure 4.4e), we notice that the financial bidcurve has lower costs than the bidcurves of the other two motive mixtures.

To compare two solutions with each other and decide which one is better, the concept of a *Pareto optimal*, or *non-dominated* solution is introduced in classical multi-objective optimization [66]. The main idea behind this concept is that a solution is Pareto optimal if none of its objectives can be improved without worsening some of the other objective values. A solution A is dominating another

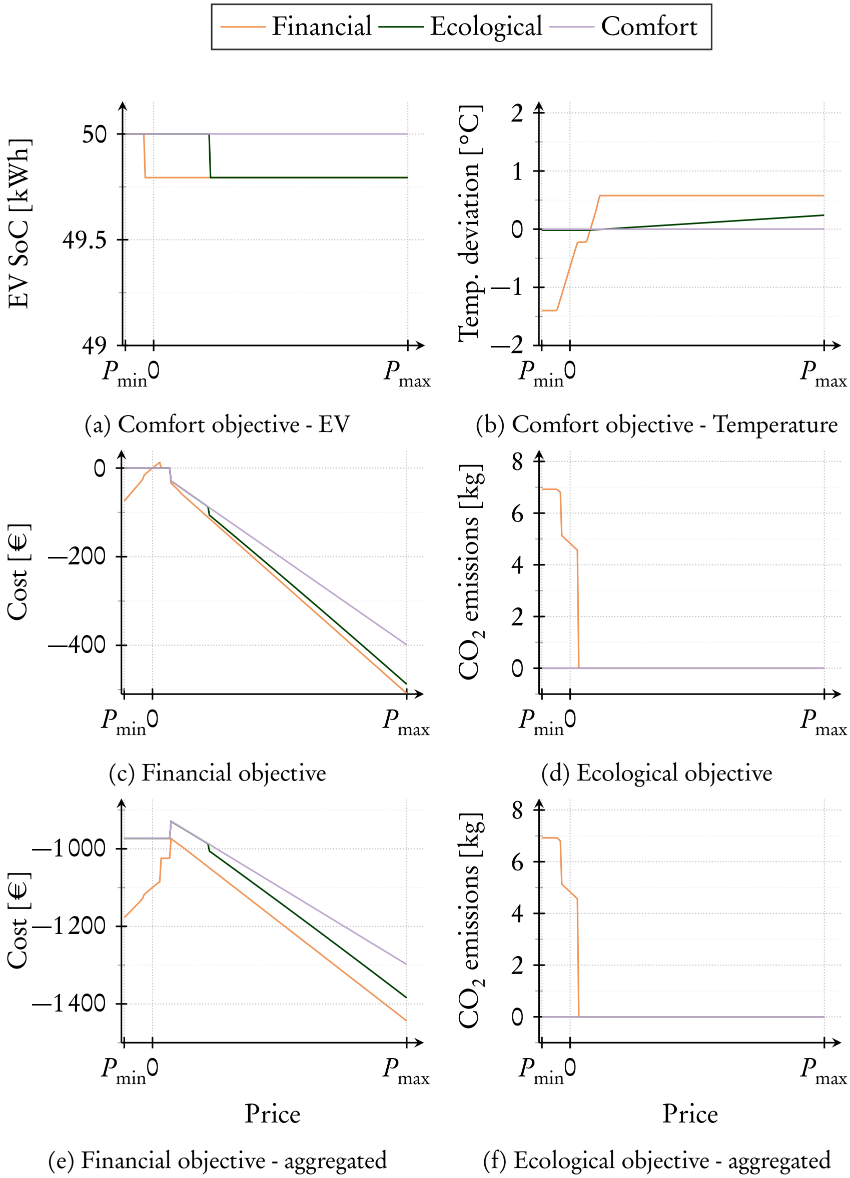


Figure 4.4: Evaluation of bidcurves (as shown in Figure 4.3e) w.r.t. the four objectives. Subfigures (e) and (f) correspond to the financial, respectively ecological, objective evaluated on the complete considered time horizon.

solution B, if all objective values of A are at least as good as the objective values of solution B, and there exists at least one objective, for which it is strictly better off. We slightly extend this concept to the comparison of two bidcurves A and B. We first define a vector a to be better than a vector b, if for all price points p, $a(p)$ is at least as good as $b(p)$, and there exists at least one price p^*, for which $a(p^*)$ is strictly better than $b(p^*)$. Based on this, a bidcurve A is dominating a bidcurve B, if for all objectives, bidcurve A is at least as good as bidcurve B and there exists at least one objective function, for which A is better than B. A bidcurve is defined as optimal if it is not dominated by any other bidcurve. Using this definition, we can now analyze whether any of the tested bidcurves is optimal.

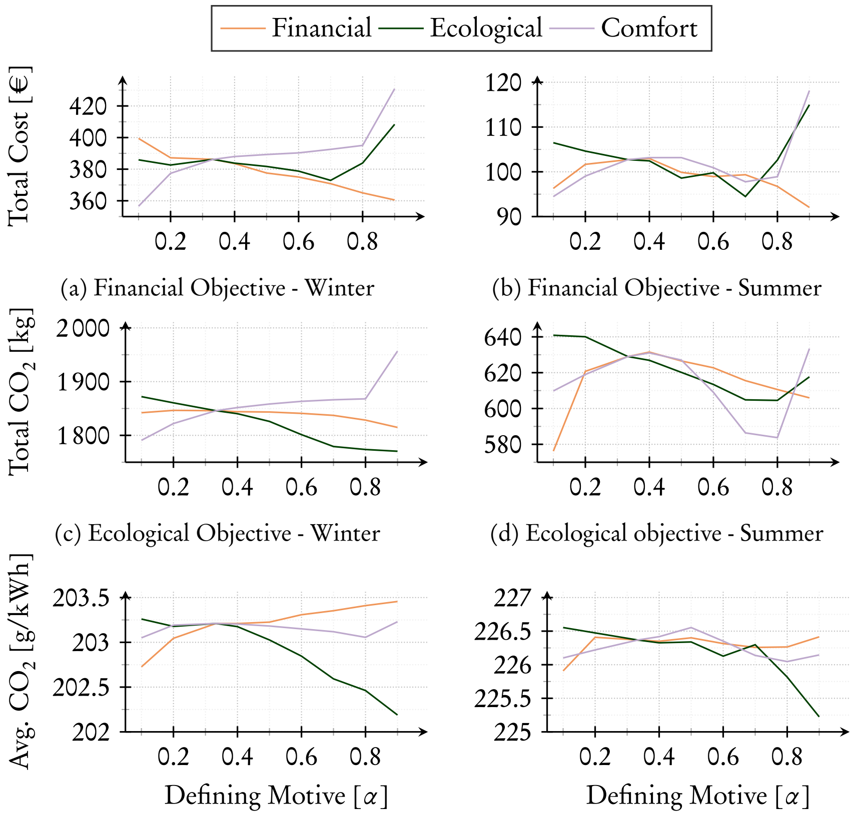
Comparing Figures 4.4a - 4.4d, we notice that no bidcurve is dominating any other bidcurve. The comfort bidcurve is clearly outperforming the other bidcurves w.r.t. both comfort objectives, the ecological bidcurve is better off than the financial bidcurve for all but the financial objective and outperforms the comfort bidcurve for the financial objective, and the financial bidcurve is better off than the other two bidcurves for the financial objective, taking the aggregated solutions into account, but clearly worse off in both the ecological and the comfort objectives. Hence, each motive achieves its intended objective and is Therefore all three motive mixtures are Pareto optimal, and no motive mixture should be preferred over the others.

4.5.4 Local Electricity Market Analysis

Going beyond the representation of human behavior for an individual household in the form of a bidcurve, in the following, we analyze the impact of human behavior for a set of households on the outcome of a LEM. As it is often difficult to estimate the individual motive mixture of households, we investigate how the market reacts to various motive scenarios across the whole parameter space of the motives, which can be represented as a 2-dimensional space, such that $a + b \leq 1$. For that matter, we introduce 3 scenario lines, each corresponding to one defining motive with weight α, while the remaining two motives evenly split up the remaining weight (such that all add up 1). Each simulation run was conducted for one week with a time slot length of fifteen minutes, resulting in 672 runs of the LEM. Two weeks, one winter and one summer week, are chosen based on outside temperature and solar irradiance.

Results

Fifty simulations are run in total, whereby each of the twenty-five motive scenarios (the balanced is identical for all) is used once for the winter and once for the summer week. Figure 4.5 shows the results of the various scenarios regarding the cost and the CO_2 emissions. Figure 4.6 displays the grid-oriented metrics, namely how often the consumed power was within 5% of the grid limit as well



(a) Financial Objective - Winter

(b) Financial Objective - Summer

(c) Ecological Objective - Winter

(d) Ecological objective - Summer

(e) Avg. ecological objective - Winter

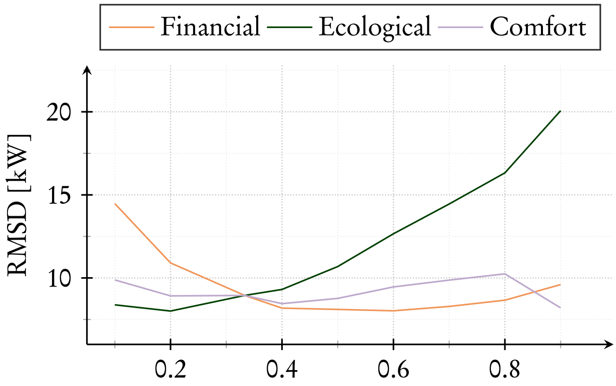
(f) Avg. ecological objective - Summer

Figure 4.5: Overview of the individual objectives for all three scenario lines for winter (left column) and summer (right column). The comfort objectives showed no unforeseen behavior and are thus left out.

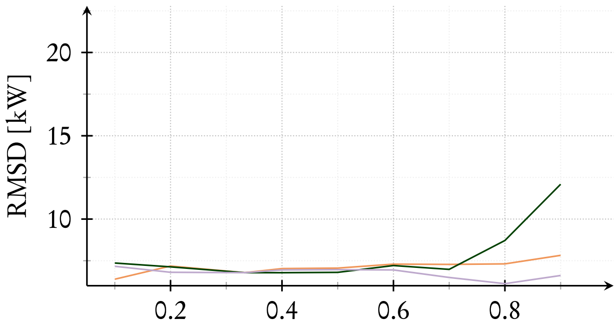
as the root-mean-square differences (RMSD), which measures the differences in power from one-time slot to the other. Given a power profile p of length T, it is computed as follows:

$$RMSD = \sqrt{\frac{1}{T-1}\sum_{i=1}^{T-1}(p(i)-p(i+1))^2}. \tag{4.6}$$

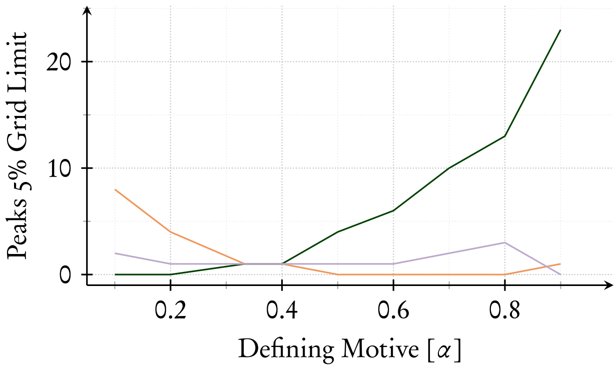
Figure 4.7 shows the overall power profile for the extreme and balanced motive scenarios for winter and summer. Note that the scales during the summer and winter weeks are different. Figure 4.8 overlays the power profile of the extreme ecological motive in summer with the CO_2 emissions as well as the power profile of the extreme financial motive.



(a) RMSD - Winter



(b) RMSD - Summer



(c) Peaks - Winter

Figure 4.6: Overview of the grid metrics for all three scenario lines. The grid limitation metric is only shown for the winter simulation, as the summer simulation showed non-zero values only for large α values for the ecological scenario line.

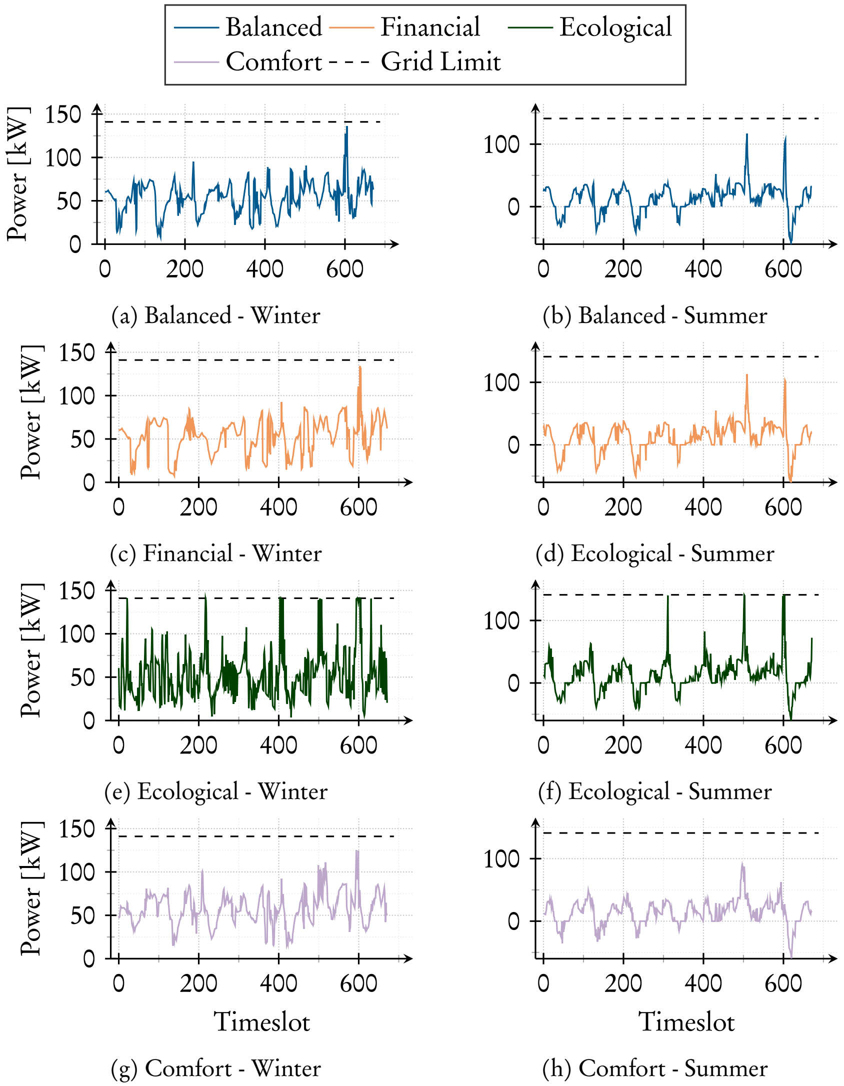


Figure 4.7: Aggregated power profile of all households for winter (left column) and summer (right column) simulations of the balanced 0.33 and 0.9 scenarios.

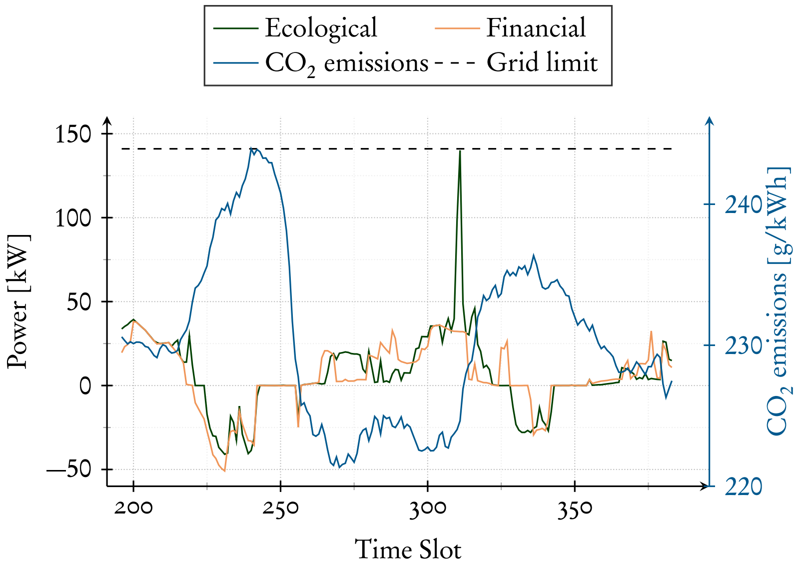


Figure 4.8: Aggregated power profile of all households for the 0.9 ecological and 0.9 financial scenarios and the CO_2 emission factors for the summer week.

Analysis

Three main insights can be observed from the results. First, based on Figure 4.5, it can be observed that, in general, the motives accomplish their respective goals. A clear trend regarding its corresponding objective can be seen for each of the three motives. In general, it holds that the higher the weight of the motive, the better the corresponding objective, independent of the summer or winter week. However, that does not necessarily imply that no other motive mixture may perform better, as can be seen for the total CO_2 emissions, in which comfort-oriented scenarios outperform the ecological motive. The considered extreme scenarios, with weights of 90% and 5%, perform the best compared to all other motive mixtures, except for the extreme ecological scenario in summer.

This outlier can be explained by analyzing how the market and HEMSs work. Given the large weight of the ecological motive, the HEMS suggests buying most of the necessary electricity at the one time slot during the considered time horizon, in which the CO_2 emission is the lowest. As the underlying CO_2 data and motive weights are the same for all households, all households want to buy a large amount of electricity simultaneously. Given these bidcurves, the LEM has to clear the market given the grid constraints, which often limits the amount of traded electricity, as shown in Figure 4.8 at time step 311 for the ecological scenario. Due to this electricity limitation, households are forced to consume less during this time slot and therefore have to shift their electricity to buy at a later time, in which the CO_2 emissions are already higher. Other motive mixtures with a smaller weight on the ecological motive do not strictly aim to buy electricity at one specific time slot, resulting in solutions in which electricity is already bought beforehand, e.g., at time slots 280 - 300 in Figure 4.8, in which the CO_2 emissions are lower. Hence, the problem of the ecological motive is the focus on buying at specific time slots coupled with the market clearing of the LEM, potentially resulting in worse ecological results compared to other motive mixtures.

This analysis of the extreme ecological motive also explains why more balanced motives usually perform quite well regarding all considered objectives. As no single motive dominates the others, the bidcurves allow a larger range of flexibility w.r.t. buying and selling electricity, which works better for the LEM clearing mechanism. In addition, devices such as batteries, EVs or the buffer tank of the HP provide enough flexibility to buy electricity beforehand and only use it later on. This also explains the good performance of the 0.6 to 0.8 comfort scenario for the total CO_2 emissions for summer Figure 4.5f. Instead of trying to sell surplus PV generation, as done by the financial or the ecological scenarios, it stores it in the EV battery or the HP. It can thereby reduce the total amount of electricity to buy compared to, for example, the 0.8 ecological scenario. Hence, even though, in total, it consumes more electricity to run the HP or charge the EV, it needs to buy less from the LEM, resulting in lower CO_2 emissions.

The second observation is based on a grid-oriented view of the outcome of the LEM. Human preferences and behavior affect the LEM beyond individual objectives. When analyzing the resulting power profiles, as displayed in Figure 4.7, large differences in the quality of the profiles can be observed. In particular, the extreme ecological scenario for the winter week, see Figure 4.6c, seems to perform quite poorly, with many large fluctuations and peaks. Such peaks in power profiles can be explained due to homogeneous bidcurves over many households, which are caused by the usage of the same data and underlying optimization models. Figure 4.6 also summarizes the power profile for each scenario into a single value using the RMSD (see Equation 4.6). These values confirm that the ecological motive is worse in winter and summer than the power profiles of the financial, comfort, and balanced scenarios. The results also show that, in particular, during the summer, the differences in traded electricity between neighboring time slots are much smaller than in the winter week. This insight aligns with the observations of the power profiles in Figure 4.7.

The third observation combines the results of the previous analysis in that even though the LEM may not perform well for extreme cases, it is generally robust against smaller deviations in the motive mixture. In particular, for scenarios where no single motive is larger than 0.7, all considered metrics, both from a grid perspective and the objectives from a household perspective, do not change rapidly and show nearly constant behavior. Only the ecological motive may still cause problems due to its focus on specific time slots, which counteracts the goal of a LEM in distributing flexibility across time.

4.5.5 Implications on Future Market Design

Summarizing the results of the previous section, we have seen that different motive mixtures can successfully model human behavior and, in turn, significantly impact the outcome of a LEM, both on an individual level, as well as on a grid level. In the following, we look at the implications of this for the application and design of future LEMs.

First of all, research on household participation in local energy trading and market approaches has identified multiple drivers of participation in LEMs or local trading approaches, ranging from environmental [80], to financial [123] or self-supportive (autarky) reasons [96]. Hence, allowing households to follow their preferences regarding local trading may enlarge the group of potential participants compared to a fixed (black box) approach. This increase in participation aligns well with the European Union's Clean Energy Package [76]. However, based on the observations and analysis of the results in the previous section, allowing households to follow their preferences may result in additional grid congestion. Therefore, LEM operators must pay close attention to the chosen distribution of the motive weights to ensure a well-working market. This could be achieved by, e.g., limiting extreme motive weights on a household level, restricting the averaged motive weights over the whole set of participating households, or implementing a default mixture, which comes in place in case the grid gets strained for a longer period of time.

Another important insight from the above results can be gained when analyzing the impact of various motive mixtures on the LEM. We have seen that even if the motive objectives do not directly align with the steering signals of the market, the LEM can still produce promising results, as seen for the results of the comfort motive. However, this effect only occurs when the steering signals and the motive objectives are not opposing each other. In the case of the comfort motive, the objective is to consume a sufficient amount of electricity, but the time of consumption is largely not important, while the steering signals focus on when to buy electricity. If, however, the motive objective and the steering signal directly oppose each other (as observed and analyzed for the ecological objective), the steering function of the market becomes ineffective. This highlights the need to pay special attention to the design of the objective function behind the various motives.

In the proposed approach, the households were given a choice between three different motives. However, they could not change the underlying objective functions on their own. Hence, it is possible to alter the underlying objective functions of motives to better align them with the steering signals of the market without deviating too much from the motive. For the ecological motive, an alternative objective could be to maximize the consumption of your own PV generation instead of only considering CO_2 emissions. If the CO_2 emissions should stay the main focus of the ecological motive, a discretization of the CO_2 emissions into pre-defined levels, such as *high*, *medium*, and *low* could shift the focus from a single time slot to a larger set of time slots, which allows the steering signal of the LEM to better reach their goal within each of the levels.

4.6 Conclusion

This chapter aimed to model human preferences and behavior and analyze their impact on the outcome and performance of a local electricity market (LEM). This was done by exploring various motives and preferences behind human behavior and using the Attitude-Behavior-Context (ABC) model from social sciences to combine internal motives with the external flexibility of devices, such as PV systems, EVs, or batteries, to create individual bidcurves for each household. We translated the ABC model into a multi-objective optimization model, which serves as the core of a HEMS and allows households to input their personal preferences and motives. The main idea behind this mathematical formulation is that the internal motives and preferences of humans are represented using a sum of weighted objective functions, while the external flexibility and access to devices and technology is modeled via constraints of the optimization problem. Within a case study, we compared the resulting bidcurves with the findings and characteristics of the ABC model and analyzed the bidcurves from a multi-objective point of view. Finally, a sensitivity analysis of the input space of the HEMS parameters gave insights into the connections between motives and their impact on the outcome of a LEM.

In a first step, it was found that the multi-objective formulation matches well with the characteristics and the core claim of the ABC model, as highlighted in other case studies. We can thereby explain the interactions between internal motives and external devices and their joint influence on the bidcurve on an individual household level. In the multi-objective analysis, we gained insights into the working of the mathematical formulation and could show that the bidcurves align with their intended weighted objective function. In addition, no motive weight combination was dominant over the others, highlighting that each motive fulfills its purpose. Focusing on the working of those bidcurves within the context of a LEM, we could observe that for the ABC model, the achieved power profiles align well with the goals of the underlying motives and that a balanced motive mixture accounts for both the individual objectives and the grid constraints. On the other hand, extreme cases and a large weight for the ecological motive can lead to large fluctuations and peaks due to synchronized bidcurves, which are often not desired. The analysis highlights the importance of aligning market steering signals with the participants' motives in future LEM design to ensure a functioning market, as misalignment can lead to undesirable results. Another key insight is the importance of thoroughly analyzing the interactions between objectives and their implementation to avoid undesirable side effects and ensure optimal bidding strategies, such as e.g., for the ecological motive.

Some limitations to this chapter should, however, be mentioned. First, the results are based on two simulated weeks with slightly simplified devices. A longer simulation with more detailed devices may provide more details and could alter the conclusions of this chapter. Second, this research focused on household bidding in a LEM rather than on the bidding of the energy providers and other strategic bidding possibilities. Thirdly, only one type of LEM was considered, and different results and conclusions may be found with different LEMs. Fourthly, we assumed human behavior to be static, that is, households do not change or adjust their parameter setting over time or react to previous (undesired) outcomes. This choice was made to reduce the additional complexity of the considered problem and also to avoid the problem of specifying when households start changing their motive mixture. In practice, this may happen, however, it has also been shown that only a relatively small percentage of people (10—15%) actually change their behavior based on feedback and messages [234]. Finally, we realize that human preferences and behavior are already complex to research in real life, and it is even more challenging in simulations where minor omissions can influence the results considerably.

Nevertheless, we believe that the conclusions and results of the analysis are relevant and that future research on LEMs should consider the impact of human preferences as an important aspect. Using the ABC model to include individual motives and preferences as parameter choices of the HEMS is a practical and reasonable approach. Finally, given these insights and conclusions, some interesting research directions for future work arise. Firstly, a study or survey could be done regarding the distribution of the motive weights. In addition to the three considered motives, other driving factors may be identified. Secondly, it may be of interest to extend and thoroughly analyze the chosen price dynamic and investigate the impact on the financial objective. A last research direction could investigate the impact of the similarity of the motives on the outcome. Within the sensitivity analysis, the motive mixtures of each household were the same, while in practice, the motive mixtures may change from one household to another. It would be interesting to investigate whether this would further impact the LEM.

5

Uncertainty: Day-ahead and intraday management for a microgrid

Abstract – *In this chapter, the second aspect, namely uncertainty in data and how to deal with it, is investigated. There are multiple tools from optimization, which are able to deal with uncertainty, such as stochastic programming or robust optimization. Due to its focus on feasibility as well as the requirements on (statistical) knowledge of the uncertainty, robust optimization is chosen as the method to deal with the uncertainty in local energy management and trading problems. Two main different robust approaches are proposed and analyzed in detail.*
The first one is a linear decision rule (LDR) approach, which is scheduled to run once a day. Replacing some of the decision variables with functions depending on the realizations of uncertain parameters allows to adapt the solution to observed realizations. The second approach combines a static robust optimization approach with a classical rolling horizon framework. The repeated solving processes of the rolling horizon allows the usage of updated forecasts and parameter, which leads to significant improvements in the objective value. The main idea behind the classical rolling horizon framework is generalized by allowing a tailor-made scheduling of the individual iterations. This additional flexibility results in substantial improvements over the classical rolling horizon framework. The last presented approach develops the tailor-made rolling horizon idea even further by adding an online aspect. This online rolling horizon framework decides on the fly whether to start an iteration or not and can thereby react to unusually good or bad forecasts and observations.

This chapter is based on [JH:3], [JH:4] and [JH:6].

5.1 Introduction

The second large conclusion of Chapter 3 is that most local energy trading approaches do not take the uncertainty in demand, generation, or prices into account and assume perfect knowledge for these values. While this assumption may be reasonable for a very short-term control problem, in a day-ahead and intraday setting, uncertainty plays a large role in important parameters defining the boundaries of feasibility and optimality.

As uncertainty on a household level, in particular, the household demand is often very difficult to predict, we focus on the joint participation of a set of households in the form of a microgrid in various electricity markets. This allows us to group the demand uncertainty of several households together and also enables (indirect) trading between households of the microgrid without explicitly creating a peer-to-peer trading market. In addition, the joint decisions allow for a participation in classical electricity markets due to the larger amounts of electricity that are bought or sold compared to a single household.

The setting considered in this chapter can therefore be described as an energy management problem for a residential microgrid under uncertainty. We assume that the microgrid has access to two different electricity markets, namely the day-ahead and the intraday market, and the planning is carried out for a discretized time horizon $\mathscr{T}$ of up to one week. The operation problem is defined from the perspective of the microgrid operator (MGO), which is responsible for fulfilling the electricity demand of all members of the microgrid. To ensure this, for each time slot of the considered time horizon, the electricity supply has to be at least as large as the occurring demand. Hereby, the MGO acts at the electricity markets as a representative of the microgrid to buy and sell electricity, as well as to manage certain devices, such as a communal battery, within the microgrid. We assume that households may be equipped with a PV system and an EV in addition to their inflexible household load. The goal of the microgrid is to minimize the electricity costs of the whole microgrid. See Chapter 2 for further details on the microgrid, as well as mathematical formulations of the constraints and the objective.

Throughout the last decade, much progress has been made within the area of energy management or trading approaches (see e.g., [70, 79, 206, 277] for recent survey papers and literature studies). Throughout some parts of this research, different techniques, ranging from rolling or receding horizons to adaptive robust optimization or stochastic programming have been successfully applied to tackle the uncertainty within such problems. The advantage of the rolling horizon approaches lies within the repeating solving of subproblems of the original problem (see e.g., [68, 69, 152, 196, 201, 225, 242]). In each solving process, which we denote as an iteration of the rolling horizon, updated forecasts and new information of uncertain data may be used to improve the resulting solution. Mathematical techniques, such as robust optimization or stochastic programming on the other hand directly focus on the feasibility of the resulting solution by using additional information on the uncertain data, such as underlying probability distributions or uncertainty sets. These techniques have become quite popular for applications within the energy domain as they match well with the feasibility focus of the current energy system (see e.g., [13, 27, 48, 181, 213, 275, 281]). One way how to combine the advantages of robust optimization and the rolling horizon is to use robust or stochastic techniques as solution techniques for the iterations of a rolling horizon (see e.g., [42, 53, 57, 89, 125, 139, 167–169, 191, 226, 270]). This allows the use of updated (real-time) information on uncertain data to incorporate the uncertainty and reduce stochasticity.

In this chapter, we present two main research directions dealing with dynamic energy operation problems under uncertainty. The first direction uses the technique of linear decision rules (LDR) from adaptive robust optimization to postpone some of the decision-making until a later point in time, where additional knowledge of previous realizations of the uncertainty is known. The core idea of LDRs is to replace some of the variables, whose decision can be postponed for some time, by a (linear) function of the uncertainty, which realizes up to the point in time when the decision has to be made. The analysis focuses on various LDR formulations and their performance. The second research direction uses the combination of (static) robust optimization with a rolling-horizon framework. In a first step, we analyze the impact of uncertainty on the rolling horizon solution and observe that the PV and EV demand uncertainty positively contribute to the objective value. This improvement stems from the time-dependency of the PV and EV uncertainty, and based on this insight, we generalize the core idea of the rolling horizon framework by allowing a more flexible scheduling of the iterations. We design an offline tailor-made scheduling algorithm, which is loosely based on two combinatorial optimization problems and which identifies promising starting time slots for the iterations of the generalized rolling horizon framework. We test the scheduling algorithm and discuss its advantages and disadvantages. Based on this discussion, we extend the generalized rolling horizon model a second time and propose an online version of the scheduling algorithm. The online scheduling algorithm is inspired by solution approaches of classical online optimization problems and decides on the fly whether to start an iteration of the rolling horizon or not.

The remainder of this chapter is structured as follows: In Section 5.2 we first introduce robust optimization techniques, before presenting the considered uncertainty. In Section 5.3 we present the LDR-based approach and analyze the impact of different LDR formulations. The second solution approach starts in Section 5.4, where we propose and test the rolling horizon-based robust energy operation problem. Based on the results, we further develop, test, and analyze this concept in Sections 5.5 and 5.6. We conclude this chapter in Section 5.7 with an outlook on possible future work and other application scenarios of the proposed approaches.

5.2 Uncertainty

In the following, we introduce and present some of the used techniques from robust optimization. Afterward, we focus on the various sources of uncertainty in the considered energy operation problem and present the used uncertainty sets.

5.2.1 Robust Optimization

Robust optimization is one of several mathematical techniques to deal with uncertainty in optimization [15]. It strongly focuses on the feasibility of the resulting solution, independent of the realization of the uncertain parameter. In contrast to other techniques, such as stochastic programming or chance-constrained optimization, robust optimization does not require detailed statistical information and knowledge, such as probability distributions of the uncertainty, which in practice is often difficult to acquire. Instead, it is based on so-called *uncertainty sets*, that are made up of all possible (or highly likely) realizations of the considered uncertainty [23]. Given these uncertainty sets for all considered uncertain parameters, the goal of robust optimization is to find the best solution, which is feasible for all possible realizations of the uncertainty sets. There are two main directions within robust optimization, namely *static* and *adjustable* robust optimization.

Static Robust Optimization

In static robust optimization, all decisions within the optimization problem are made directly, that is no decision is postponed until a later stage. Usually, the uncertainty sets are associated with some of the parameters of the constraints or the objective of an optimization model. The core of static robust optimization is a set of techniques to integrate these uncertainty sets into the constraints of the mathematical model. These techniques allow for a reformulation of the original constraints into a robust counterpart, which includes the uncertainty sets directly into the constraints. This reformulation heavily depends on the uncertainty sets, and for some well-known and studied classes of uncertainty sets, such as box, budget, ellipsoidal, or polyhedral uncertainty sets, the reformulation results in a tractable robust counterpart [83]. However, it should be noted that the resulting formulation usually increases the size of the model significantly, both in the number of variables and constraints.

An advantage of static robust optimization is the focus on feasibility, which aligns well with the operation of the electricity grid. In addition, the resulting formulations often result in tractable models, which can still be solved in practice. A well-known disadvantage of robust optimization is that solutions tend to be very conservative, as it is unlikely that all uncertain parameters realize at their worst case. One way to reduce this conservatism is offered by adjustable robust optimization, in which a part of the decisions can be postponed until some of the uncertainty is already revealed.

Adjustable Robust Optimization

Adjustable robust optimization can be seen as an extension of static robust optimization into multi-stage decision-making [21, 269]. It splits up the decisions into two parts. The first part consists of *here-and-now* decisions, which similarly to static robust optimization directly have to be decided upon. The second part consists of *wait-and-see* decisions, for which the decision can be postponed until a later point in time. Thereby, the algorithm can first observe and still react to the realizations of (some) uncertain parameters, before making their final decision. There are two main research directions within adjustable robust optimization, one focusing on exact solution approaches, and one on decision rule-based approaches.

The exact solution approaches are often derived for two-stage robust problems and are based on a decomposition of the problem into a first and second-stage model. The solution process is usually based on iterative techniques such as Benders decomposition approaches [27], constraint and column generation techniques [271] or combined cutting plane and alternating direction algorithms [167].

The second direction, which focuses on decision rules, directly makes use of the split of the decisions into here-and-now and wait-and-see variables to reformulate the adjustable robust model into a static one. It does so by replacing the wait-and-see variables with an arbitrary function, which depends on the realization of (some parts of) the uncertain data. However, optimizing over functions of arbitrary form is intractable, and therefore, the functions are often restricted in their form. One common function is an affine one, leading to (affine) LDRs [21]. It has been shown that in practical application, such LDRs often perform very well [22], and under certain assumptions on the uncertainty sets and the original model formulation it may even be optimal [25]. However, one limitation of such LDRs is the representation of integer wait-and-see variables, as such variables are replaced by affine linear functions, which may not provide an integer solution.

Another widely adopted, yet rather heuristic approach to robust multi-stage decision-making is to combine static robust optimization with a rolling horizon framework. This combination not only allows to reoptimize the wait-and-see decisions multiple times until their deadline but also allows to use updated uncertainty sets in later iterations of the rolling horizon. For a detailed introduction to the individual techniques and applications, we refer to [20].

5.2.2 Sources of Uncertainty

Due to the different time scales, for which decisions have to be made on the two markets and on the device level, as well as the intermittent nature of renewable energy sources and human behavior, some of the parameters within this planning problem are difficult to predict and deviations from predicted values may appear. In the following, we present the different sources of uncertainty considered within this thesis:

- *Load*: The household load strongly depends on the behavior and actions of the residents, which can be subject to sudden changes, which are not perfectly predictable (see e.g., [4]).
- *PV generation*: Even though (PV) forecasting methods are getting better, it is not possible to perfectly predict the PV generation for multiple days in advance (see e.g., [101]). Hence, PV generation is subject to uncertainty, whereby short-term forecasting often is more accurate than long-term forecasting of 24 hours and more.
- *EV demand*: Even though the electricity demand for driving a certain distance can be computed quite accurately, in practice various aspects, such as the outside temperature, vehicle heating or cooling, or the traffic, influence the actual demand (see e.g., [81, 264]).
- *EV arrival and departure times*: In settings with short time slots, such as e.g. 15 minutes, already smaller deviations due to crowded roads may lead to uncertainty in arrival or departure times. In addition, unplanned events like working longer, or a small detour to a supermarket can be other sources of uncertainty.
- *Market prices*: The prices of both considered markets are dependent on demand and supply, which are both not perfectly predictable, leading to fluctuations in the prices (see e.g., [116, 154, 258]).

5.2.3 Modeling of Uncertainty

To integrate the considered uncertainties into the model presented in Chapter 2, we first introduce the types of used uncertainty sets for the different uncertain parameters. We start with standard uncertainty sets, which make up the core of any robust optimization approach. There are a couple of well-studied uncertainty sets, for which tractable robust counterparts have been established. See [26, 84] for further information and a detailed introduction to static robust optimization. For our model, we make use of two uncertainty sets, namely the budget and the box uncertainty set:

- *Box uncertainty set*: The EV demand is an example of a box uncertainty set. Assume that for an EV h, the demand $p_t^{EV,h} > 0$ in time slot t is positive. Then due to various reasons, there may be a (small) deviation of the used energy from the expected value $p_t^{EV,h}$. Rather than defining an uncertainty interval for all possible values of this parameter, we first split the EV demand up into a certain, known part and an uncertain part

$$p_t^{EV,h} = \hat{p}_t^{EV,h}(1 + \alpha_t^{EV,h} u_t^{EV,h}),$$

where $\hat{p}_t^{EV,h}$ corresponds to the expected or predicted part and $\alpha_t^{EV,h} u_t^{EV,h}$ models the uncertain part, with $u_t^{EV,h} \in [-1, 1]$ being a random variable to model the true realization. Furthermore, $\alpha_t^{EV,h}$ defines (together with $\hat{p}_t^{EV,h}$) how large the uncertainty interval is. Hence, the actual uncertainty is now completely covered by the variable u, and the uncertainty set for the EV demand of a given EV h is given by

$$\mathcal{U}^{EV,h} = \left\{ u \in \mathbb{R}^{|\mathcal{T}|} \middle| ||u||_\infty \leq 1 \right\}.$$

» *Budget uncertainty set*: The household load is an example of a budget uncertainty set. In addition to the box uncertainty set, the budget uncertainty set adds another constraint, which limits the number of realizations at extreme points (of the box uncertainty set). Similar to the EV demand, we first modify the uncertain parameter to

$$p_t^{L,i} = \hat{p}_t^{L,i}(1 + \alpha_t^{L,i} u_t^{L,i}).$$

Hereby the box uncertainty part of the load is modeled in the same manner as for the EV demand. We further restrict the box uncertainty set of all prosumers for time slot t by adding the following constraint

$$\sum_{i \in \mathcal{N}_{EV}} |u_t^{L,i}| \leq \Gamma_t^L.$$

This constraint ensures that at most Γ_t^L prosumers are at their own respective extreme points ($u_t^{L,i} = 1$ or $u_t^{L,i} = -1$) w.r.t. their load. Combining the constraints, we get the following budget uncertainty set

$$\mathcal{U}_t^L = \left\{ u \in \mathbb{R}^{|\mathcal{N}_P|} \middle| ||u||_\infty \leq 1, ||u||_1 \leq \Gamma_t^L \right\}.$$

The remaining uncertainty sets can be modeled similarly, with the PV generation being a budget uncertainty set, and the market prices and the EV arrival and departure times being box uncertainty sets.

To account for the change in accuracy of PV forecasting, we need to alter the PV uncertainty set slightly. We assume that the PV forecasts are time-dependent and that they improve over time, meaning that the uncertainty sets get smaller, the closer we are to the corresponding time slot. For this, we need to introduce another index for the PV data to indicate when the forecast has been made. Let $p_{t,s}^{PV}$ denote the PV generation forecast for time slot t, made at time slot $s < t$.

The same applies to $\alpha_{t,s}^{PV}$, which is predicted at time slot s for time slot t. In case only one time slot index is present, we assume w.l.o.g. that the initial forecast of the beginning of the time horizon is used. One important assumption on the resulting sequence of PV forecasts for a fixed time slot t is that they are contained in each other, i.e.,

$$p_{t,s}^{PV}(1-\alpha_{t,s}^{PV}) \geq p_{t,l}^{PV}(1-\alpha_{t,l}^{PV}), \tag{5.1}$$

and

$$p_{t,s}^{PV}(1+\alpha_{t,s}^{PV}) \leq p_{t,l}^{PV}(1+\alpha_{t,l}^{PV}), \tag{5.2}$$

for time slots $l \leq s \leq t$. This ensures that the uncertainty intervals for a specific time slot t can only improve over time.

5.3 Linear Decision Rule-Based Energy Management Approach

The first approach to deal with uncertainty in the energy management problem uses LDRs to allow for some of the decisions, such as the curtailment of PV or the charging and discharging of batteries and EVs to be postponed until a later time slot. The considered setting is as described in Section 5.1, that is households are possibly equipped with a PV system and an EV, and there is a communal battery, operated and managed by the MGO.

The resulting mathematical formulation of the base model without uncertainty has already been presented in Section 2.3. One difference to the base model is that we do not consider charging and discharging efficiencies of the EV and battery. This allows to reformulate the corresponding constraints in such a way that a single variable can represent the charging and discharging decisions of a device per time slot. A side effect of this decision is that batteries or EVs can only either charge or discharge within each time slot. In addition, we assume that the PV forecast for time slot t, made at the beginning of time slot t is perfect, that is $\alpha_{t,t}^{PV} = 0$ for all $t \in \mathcal{T}$.

Based on this setting and model, we first introduce the LDRs and their implementation into the model. We then proceed with a case study to demonstrate the practical feasibility of the proposed approach and conclude this section with a discussion of the limitations and restrictions of the proposed technique.

5.3.1 Linear Decision Rules

In the following, we present how the uncertainty of the parameters can be included in the linear decision rules to design an adaptive robust model. We use the PV system to present the linear decision rule in a more detailed way; applying them to the other variables can be done in a similar way. Given a PV system j and time slot t, the variable $x_t^{PV,j}$ describes the amount of electricity that is used, i.e. not curtailed. Note, that the decision on how much to curtail can be made directly before the time slot. Thus, the corresponding LDR for $x_t^{PV,j}$ is designed as follows

$$x_t^{PV,j}(u) = \beta_t^{PV,j} + \beta_{t,t}^{PV,j,PV} u_t^{PV} + \beta_{t,t-1}^{PV,j,L,F(j)} u_{t-1}^{L,F(j)},$$

where $\beta_t^{PV,j}$, $\beta_{t,t}^{PV,j,PV}$ and $\beta_{t,t-1}^{PV,j,L,F(j)}$ serve as the parameters of the LDR. Within this LDR, $\beta_t^{PV,j}$ represents the part of the decision, which is independent of any future realizations, while $\beta_{t,t}^{PV,j,PV}$ and $\beta_{t,t-1}^{PV,j,L,F(j)}$ represent the influence of the realization of the uncertain PV and load parameter. Note, that $\beta_{t,t-1}^{PV,j,L,F(j)}$ depends on the realization of the load uncertainty of time slot $t-1$, while for $\beta_{t,t}^{PV,j,PV}$ we assume that it is possible to perfectly predict the PV production of the current time slot t. When replacing the variable $x_t^{PV,j}$ by the LDR $x_t^{PV,j}(u)$, the parameters of the LDR become here-and-now variables in the robust model. Note that replacing every wait-and-see variable with a LDR results in a final model with only here-and-now variables, and hence well-known standard techniques from static robust optimization can be applied [20].

5.3.2 Numerical Results and Analysis

The goal of this computational study is to demonstrate the practical feasibility of the proposed approach by means of a small case study. Hereby, we focus on two main questions. The first question is how much better the LDR approach performs compared to the static robust model. In a second step, we focus more on the effect of the different components of LDRs on the objective value. Unless explicitly mentioned, we apply the linear decision rules as described in Section 5.3.1 to all decisions of the deterministic model apart from the day-ahead market variables. That is, we replace $x_t^{ID,buy}$, $x_t^{ID,sell}$, $x_t^{PV,j}$, $x_t^{B,b}$ and $x_t^{EV,h}$ each with their respective LDR.

Simulation Setup

All following simulations are based on a microgrid of 20 households, equipped with in total 17 PV systems, 15 EVs, and one communal battery system. We consider a time horizon of 1 day, consisting of 96 time slots of 15 minutes. To model the household load, we use average Dutch load profiles from the 12th to the 14th of April 2021 [187]. These profiles are scaled to a household with a yearly demand of 3,500 kWh, which results in a daily consumption of 8 to 10 kWh per household. All PV systems are modeled equal, with a production of up to 11 kWh per day. The generation profile is based on a sunny day. The EVs are based on the VW ID.3, with a battery capacity of 58 kWh and charging and discharging limits of 11 kW. The EV demand is computed based on daily trips between 20 and 70 km and an electricity usage of 18 kWh per 100 km. The jointly used battery system consists of 3 interconnected Tesla Powerwall modules with an aggregated battery capacity of 42 kWh [246]. The charging

Scenario	α^L	α^{PV}	α^{EV}	α^{DA}	α^{ID}
A	0.1	0.15	0.05	0.05	0.1
B	0.2	0.25	0.1	0.1	0.2
C	0.35	0.4	0.2	0.2	0.3

Table 5.1: Uncertainty Scenarios

and discharging power limits are 15 kW. W.l.o.g., we assume that the initial SoC of EVs and the battery is 0. The day-ahead electricity prices for the considered time horizon are taken from [72], while the intraday market prices are taken from the Dutch TSO TenneT [245].

Regarding the uncertainty, we introduce three different scenarios, A, B, and C, each representing a different level of uncertainty. The corresponding uncertainty levels are given in Table 5.1. In order to evaluate the LDR approach, we need the actual realizations of some of the uncertainty as input. In most literature on robust optimization, a uniform distribution is used to draw the actual realizations (see e.g., [13, 27]). Such a uniform distribution seems to be matching best with the assumption of having no further knowledge of the underlying distribution apart from the support. Unless mentioned otherwise, the realizations within this chapter are all drawn from a uniform distribution on the interval $[-1, 1]$.

LDRs vs. Static Robust Model

To get some insight into the working of the proposed approach, we compare the solution of the adaptive robust LDR approach with the solution of the static approach for the three different uncertainty scenarios. As the LDR approach heavily depends on the true realizations of the uncertainty, only comparing the objective values of both models with each other does not allow to draw a conclusion on the performance of the LDR approach. Hence, we will randomly draw 100 realizations of the uncertainty and use the LDRs as well as the solution of the static robust model to compute the actual costs of the approaches.

The results are displayed in Figure 5.1, where the three groups represent the three different scenarios A, B, and C. Furthermore, *Static Obj.* and *LDR Obj.* represent the objective value of the static robust, respectively the LDR model, while *Static (avg) Cost* and *LDR (avg) Cost* represent the average actual cost of the static, respectively LDRs solution, evaluated w.r.t. the 100 random realizations. Note, that due to the uncertainty in the market prices, the average actual costs of both approaches are much better than the objective value of the respective models, as these assume the worst-case realizations of the prices. Focusing on the objective values of the models first, we note that the additional flexibility gained by replacing the wait-and-see variables with LDRs already results in improvements of 10.0% to 13.1%. Comparing the average actual costs, we notice that throughout all scenarios, the LDR approach still performs much better than the static version, leading to improvements between 18.1% and 42.3%. However,

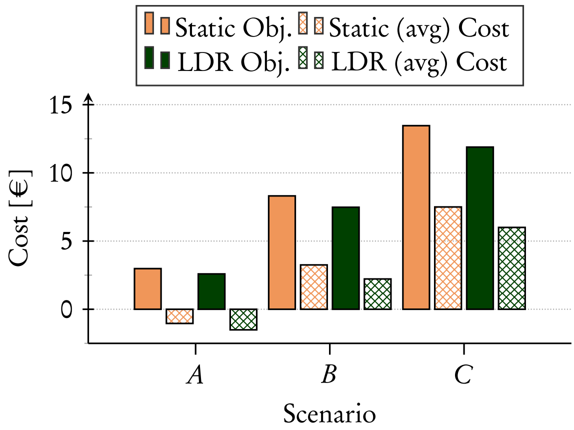


Figure 5.1: Comparison of static robust optimization and the LDR approach for various uncertainty scenarios.

note that the increase in relative improvements mainly stems from the lower cost values of the static approach compared to the objective value. That is, the absolute improvements of the objective value and the average costs are quite similar.

Structure of LDRs

One well-known issue with the LDR approach is that due to the additional variables introduced via the LDRs, there are often multiple optimal solutions. While in a deterministic setting, this issue does not matter beyond personal preferences, in the presence of uncertain parameters, these seemingly equally good solutions in the worst-case scenario may differ drastically in performance once evaluated w.r.t. the uncertainty realizations. One possibility to get a 'good' optimal solution regarding the actual realizations is the following approach, which is based on solving two similar LDR models.

1. Run the original LDR model giving the optimal objective value of the problem.
2. Modify the LDR model by adding a constraint, considering only solutions having this objective value into the model. Now replace the objective function with a function that uses e.g. average or expected prices.

Introducing the objective function as a constraint into the model restricts the set of feasible solutions to the set of optimal solutions. Solving the second model then only considers optimal solutions w.r.t. the original worst-case objective function, while also minimizing the average of the expected cost. However, it should be noted that this approach does not guarantee a better solution, as there

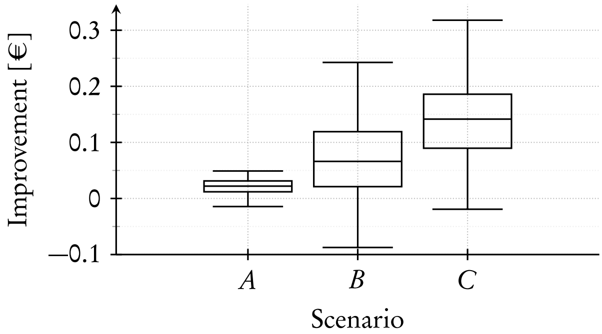


Figure 5.2: Boxplot statistics on the improvement of the modified LDR approach over the original LDR approach.

may always be realizations in which the original optimal solution performs better. Figure 5.2 displays the boxplot statistic on the improvement in the actual cost of the modified LDR approach over the original one for 100 random realizations of the uncertain parameters. As can be seen, for the vast majority of realizations, the modified LDR solution has lower costs compared to the original LDR solution, and on average, the improvement is between 1.5% and 3.14%, although for individual realizations, the improvements can be as large as 11.26%. In the following, we use the modified LDR approach.

Another well-known issue of the proposed approach is the size of the resulting formulation, which is several (hundred) times that of the static robust model. As a larger mathematical formulation often implies a longer running time of the solver, reducing the number of variables and constraints without changing the set of feasible solutions can be a first, easy step to shorten the running time. By identifying which LDRs have a larger impact on the objective value, we are able to derive more compact models that still perform better than the static robust model. To identify which LDRs have the largest impact on the objective value, we modify the full LDR model to only include LDRs for one variable type. The resulting models (PV, EV, Battery, intraday market) are tested using base scenario B. See Table 5.2 for the results.

Table 5.2: Comparison of Single LDR Models

Model	obj. value	avg cost
Static Robust model	8.31	3.25
full LDR model	7.48	2.22
PV	8.31	3.25
EV	7.76	2.75
Battery	8.31	3.24
intraday market	8.31	3.25
EV+PV+ID	7.53	2.26

Focusing on the objective values first, we notice that both, the EV model and the EV+PV+ID model, achieve nearly the same objective value as the full LDR model. The remaining single LDR models on the other hand only achieve the same objective as the static robust model. This observation can be explained by the usage of electricity. For the PV, and the intraday LDR model, the only decision they can adjust is how much they supply. However, if the consumption side is fixed, then there is no need to adjust the supply side, and therefore, we end up with a static system again. The same argumentation holds for the battery. The EV on the other hand can adjust its consumption according to the observed realizations of uncertain generation and therefore achieves a better objective value. The combination of EV, PV, and intraday market amplifies this effect, as the adjustable supply of the intraday market and the PV can match the flexible consumption of the EV even better.

Shifting the focus from the 'worst-case' oriented objective value to the actual cost, we see that all models significantly improve and that the previous observations also translate to the case of only a few LDRs. Apart from the EV model, all remaining single LDR models perform identically to the static robust model, subject to some rounding errors. When analyzing the EV+PV+ID model, which once again achieves nearly the same results as the full LDR model, we notice that the impact of the battery LDR is rather small, and it seems that the adaptive behavior for the buffer is not needed. However, it should be noted, that we allow the EVs to also discharge, and thereby they already act as batteries with limited availability during the day. Hence, only the impact of an additional battery LDR in this setting is low.

5.3.3 Discussion

Summarizing the above results and analysis, we have shown that the proposed robust approach, using affine linear decision rules performs significantly better than the static robust model, both in the objective value and the actual costs. A detailed analysis highlights the impact of individual LDRs, and we also show a way to reduce the size of the resulting static model without worsening the objective value.

However, a few limitations should still be addressed. In contrast to the EV and battery models, as introduced in Chapter 2, we did not include charging and discharging inefficiencies into the LDRs. The main reason for this decision is the required number of variables, which doubles when including these inefficiencies. As the modeling of EVs and batteries already make up a large part of the total size of the model, we have decided against this. A second limitation concerns the uncertain EV arrival and departure times. The nature of the uncertain departure times inherently does not allow to react to it, as once observed, it is already too late. Therefore, it is not possible to adjust EV charging and discharging to the uncertain EV departure times in any multi-stage solution approach. In contrast, it is possible to react to realizations of the uncertain EV arrival times, however, it is rather difficult to include those into a LDRs approach. The LDR approach is best suited for uncertainties of parameters, which are part of a constraint (or objective). The EV arrival, however, is not directly part of a constraint but defines whether a constraint is even created. Hence, the uncertainty is binary in nature, and this fundamental difference to uncertain parameters, such as the PV generation or the EV demand makes it difficult to include in a LDR. One way to include it nevertheless, is by means of multiple 'copies' of the LDRs, each one of them representing a possible arrival time. However, depending on the length of the time window in which an EV may arrive, this can easily lead to an intractable model due to the number of variables and constraints. Therefore, we once again did not include it in the LDRs. The last limitation of the LDRs focuses on the uncertainty set of the PV generation. As mentioned in Section 5.2.3, it is well known, that the accuracy of PV forecasts differs depending on the time between prediction and realization. This change in uncertainty should also be reflected in the corresponding uncertainty sets, however, neither LDRs nor static robust models allow for this representation.

These limitations directly lead us to the following sections, in which we propose a (static) robust model combined with a rolling horizon, which allows us to tackle the above limitations.

5.4 Classical Rolling Horizon-Based Static Robust Optimization

As shown in Section 5.2, next to specialized techniques, such as LDRs or other adaptive techniques for multi-stage problems, one promising approach in the literature is to combine (static) robust optimization with a rolling horizon framework. In the following, we propose and analyze such a combined approach to deal with the uncertainty occurring in energy management problems. We first introduce the concept of a rolling horizon, as used throughout the literature, before focusing on its implementation within the considered energy management and trading problem. We conclude this section with an analysis of the impact of the individual uncertainty sources on the results of the proposed approach.

5.4.1 Rolling Horizon Framework

In general, the rolling horizon (or receding horizon) approach is a popular technique in academia and industry to solve (stochastic) large-scale optimization problems over a long time horizon (see e.g., [43, 219]). Hereby in all these optimization problems, the time horizon is discretized. Instead of solving the complete problem at once, a rolling horizon approach splits the time horizon into smaller, mostly overlapping time windows and solves the problem iteratively for these time windows. We refer to solving the problem for one such time window as an iteration of the rolling horizon approach. Usually, there are two main parameters characterizing the rolling horizon framework. The first one is the step size, which defines the distance between the starting times of two consecutive time windows and the second one is the length of the time windows. To cover the complete time horizon without gaps, it is obvious that the step size has to be smaller or equal than the time window length. Note, that in case the step size is smaller than the window length, only the partial solution up to the starting time of the next time window is realized.

Combining a rolling horizon framework with robust optimization ensures a feasible solution while reducing the considered uncertainty in data due to the shorter time horizons of the time windows. In addition, it allows for a natural integration of the realization of uncertain parameters into the decision-making process. This makes it possible to react to observed realizations of uncertainty even when using static robust optimization. Hence, the combination of static robust optimization and a rolling horizon framework yields similar properties compared to adaptive robust approaches while avoiding some of the additional computational complexity issues associated with adaptive robust techniques (see e.g., [21, 84]). Another advantage of the combination of static robust optimization and a rolling horizon framework is the reduced communication between households and the microgrid, which is only needed when an iteration of the rolling horizon is started. This allows to limit the exchange of information to a fixed number of iterations per day.

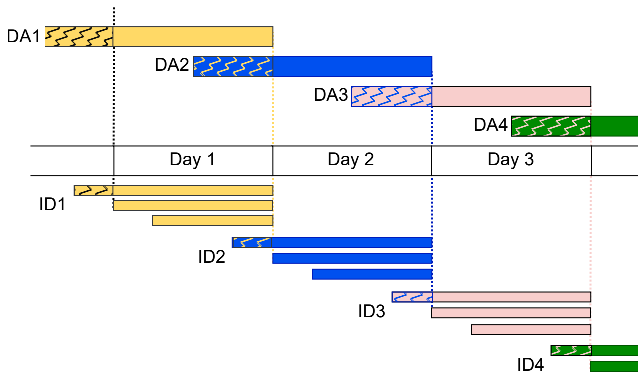


Figure 5.3: Market Decisions: The upper level displays the iterations of the rolling horizon, which is responsible for the decisions of the day-ahead market. The first part of each rolling horizon iteration represents the already fixed day-ahead market decisions of the previous iteration. The bottom part displays the folding horizon iterations and its decisions regarding the intraday market and devices.

In the context of the energy setting, we have to take the characteristics of the considered devices and entities into account when designing the rolling horizon framework. The day-ahead market, as introduced in Section 2.2, has the largest influence on the design of the rolling horizon due to its working and timing.

The energy trading decisions of the day-ahead market for a whole day have to be submitted the day before at 12:00, leading to a time window of at least 36 hours to cover the whole next day. As day-ahead market decisions need to be submitted every day, we already have a rolling horizon framework with a step size of 24 hours and a time window length of 36 hours to participate in the day-ahead market. In between these day-ahead market decisions, we propose a folding horizon approach to adapt the short-term decisions of the intraday market and the considered devices to observed realizations and updated forecasts of the uncertainty. Within the folding horizon, the step size, ranging from 15 minutes to 1 day, is used to schedule the folding iterations. Note that the end of the time window is equal to the end of the last submitted day-ahead market decision, leading to time window lengths between 12 and 36 hours, see also Figure 5.3. Within the folding iterations, the day-ahead market variables are already fixed to the previously submitted decisions. In the following, we do not explicitly differentiate between iterations of the rolling and folding horizon, and use the term rolling horizon iteration for any iteration in the combined approach. The pseudo-code of the rolling horizon implementation can be seen in Algorithm 2.

Algorithm 2: Classical Rolling Horizon Approach

for $t = 1$ to T with step size t_0 **do**
    solve *staticRobustModel(t,data)*;
    reveal uncertainty realizations in $[t, t + t_0)$;
    compute and fix new initial values in *data*;
    if t starts at 12:00 **then**
        fix day-ahead market decisions for the following iteration;
    save the decisions in $[t, t + t_0)$ to *final decisions*;
compute the actual costs based on the realizations and the decisions from *final decisions*;
Result: costs and *final decisions*

5.4.2 Numerical Results and Analysis

Simulation Setup

All following numerical experiments within this section are based on the same simulation setup and data as already presented in Section 5.3.2. We restrict this first analysis to the standard uncertainty scenario B and consider a time horizon of 3 days, discretized into 15-minute time slots. The standard microgrid again consists of 20 households with in total 15 EVs, 17 PV systems, and one communal battery system. One important difference to the previous simulation setup is the usage of charging and discharging efficiencies for the battery and the EVs. We assume an efficiency of 95% for both charging and discharging of EVs and batteries, leading to a round trip efficiency of about 90%.

Results and Analysis

Starting with base scenario B, we first compare the objective values for various step sizes of the rolling horizon model with the fully static model, which solves the complete time horizon of three days at once. The tested step sizes in time slots are $|\mathcal{T}|$, 96, 48, 24, 16, 12, 8, 4, and 2. Note that the step size $|\mathcal{T}|$ solves the fully static model at once, while the step size of 96 implies that the iterations of the rolling horizon model are equivalent to the decision-making time slots of the day-ahead market, that is at 12:00 on every day, as well as at the first time slot of day 1 to initialize a solution (see also Figure 5.3). To account for the influence of random realizations of the uncertainty, we run the models 5 times and focus on the averaged values, as shown in Table 5.3.

Table 5.3: Comparison of step sizes, the fully static model, Scenario B

Step size	avg. obj. value	abs. improv.	rel. improv.
$\|\mathcal{T}\|$	4.6367	0.000	0.0%
96	4.9705	-0.3338	-7.2%
48	4.3666	0.2701	5.8%
24	4.2409	0.3958	8.5%
16	3.9931	0.6436	13.9%
12	3.6239	1.0128	21.8%
8	3.3367	1.3000	28.0%
4	1.9621	2.6746	57.7%
2	0.9762	3.6605	78.9%

As can be seen, the rolling horizon model significantly outperforms the fully static model (denoted by $|\mathcal{T}|$ in Table 5.3) for each of the considered step sizes smaller than 96. In addition, the smaller the step size, the larger the improvement gets over the fully static model. At first glance, this seems counterintuitive, as the fully static model has access to information over all time slots at once, while in the rolling horizon setting this information is distributed over multiple iterations. Given that some of the constraints (EV and battery) connect consecutive time slots, one may expect that not having full information at once should lead to worse solutions. However, the structure of the uncertainty allows for additional uncertainty information within the individual iterations, decreasing the impact of the distributed information over the whole time horizon.

In the following, we discuss the impact of the individual uncertainty sources on the objective value to identify which of the underlying uncertainties are responsible for the observed improvements. In a first step, we verify the statement regarding the optimality of a rolling horizon by running the same instance, but without any uncertainty, apart from the market data. Afterward, to analyze the impact of uncertainty in more detail, we create four new scenarios, in which we always add only one uncertainty source (EV arrival, EV demand, PV, and load)

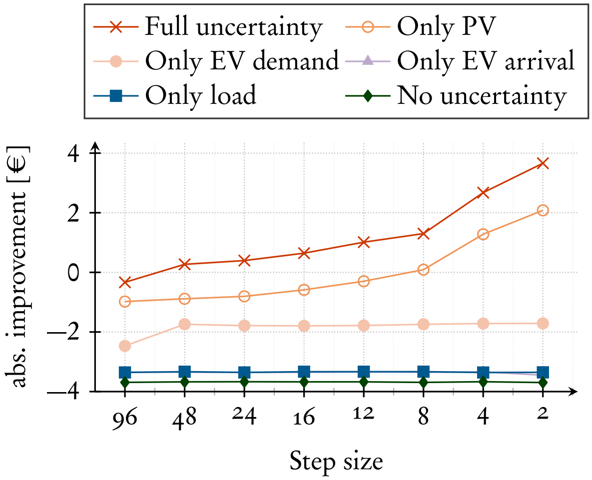


Figure 5.4: Absolute improvements of different step sizes over the fully static model for different uncertainty configurations and step sizes.

to the instance without any uncertainty. In Figure 5.4, the absolute differences in the average objective value of the five modified scenarios for the various time steps with the fully static model are given. For a better comparison, the above-presented results for the base scenario B are added to Figure 5.4, denoted by *full uncertainty*.

» The modified scenario with *no uncertainty* (rhombi in Figure 5.4) shows the previously anticipated results that the rolling horizon models with multiple iterations perform worse compared to the fully static model solving the problem once for the whole time horizon. This difference in objective value is attributed to the shorter time horizons of the iterations of the rolling horizon model. Instead of having access to all data and solving all three days at once, the individual iterations of the rolling horizon only consider 12 to 36 hours in advance. This limited information per iteration leads to suboptimal solutions.

» In case, all parameters apart from the *EV arrival* (and departure) times are known beforehand, (triangles), the fully static model still performs significantly better than any rolling horizon model (see Figure 5.4). Comparing the differences to the scenario without any uncertainty, some small improvements can be observed. These improvements can be explained by the updated information on EV arrival times, which may result in longer periods where an EV can be charged or discharged compared to the worst-case arrival times.

» For the second uncertain EV parameter, the *EV demand* (circles), the rolling horizon model still performs worse than the fully static model for all step sizes. However, it performs significantly better than the previous cases of no uncertainty or uncertain EV arrivals (see Figure 5.4). This improvement follows from how robust optimization deals with the uncertain EV demand. As the solution has to be feasible for every possible realization of the demand, the achieved solution charges at least the maximum demand for the next trip. However, within the rolling horizon approach, at some iteration, the true EV demand is revealed. As the true realizations are drawn uniformly at random from the uncertainty sets, the realized EV demand is, in expectation, smaller than the maximum demand. The resulting surplus in the EV battery can now either be sold at one of the electricity markets or future charging may be reduced. This also explains the differences in improvement between a step size of 96 and the remaining (smaller) step sizes, as these can still react to the last EV demand realizations during the last day.

» The modified uncertainty scenario with *only PV* uncertainty (empty circles) is the only scenario apart from the full uncertainty scenario, in which some of the rolling horizon models outperform the fully static model. These improvements can be explained as follows: Due to the dynamic uncertainty sets of the PV production, the models get access to additional information in the form of smaller PV uncertainty sets for the next few time slots during each iteration. Therefore, the solutions of the iterations can make better decisions regarding the usage of the PV generation. The smaller the step size of the rolling horizon model, the more often the model gets access to this additional information, and the better the results.

» The last uncertainty scenario considers only the household *load* to be uncertain (squares). As can be seen in Figure 5.4, the rolling horizon models do not perform any better than the fully static model. This can be explained by the fact that no further information on future uncertainties becomes available over time. Therefore, observed realizations do not lead to additional useful information for the rolling horizon models.

When analyzing Figure 5.4 in more detail, we notice that the shape of scenario *B* (full uncertainty) is a composition of the scenarios considering only uncertain EV demand or uncertain PV generation. The first sharp improvement from step size 96 to 48 can be mainly attributed to the observations of the uncertain EV demand, while for the remaining step sizes, the shape of the curve resembles the shape of the PV scenario.

5.4.3 Discussion

Summarizing, we note that mainly two uncertain parameters are responsible for the improved performance of the classical rolling horizon model, namely the EV demand and the dynamic PV uncertainty sets. In its base, the rolling horizon-based approach allows to better adapt to uncertainty realizations as well as improved forecasts. The above analysis, therefore, strengthens our choice of a rolling horizon as a suitable framework for modeling and analyzing uncertainty in energy management and trading systems. The results also show that the step size has a significant impact on the quality of the results and that smaller step sizes generally lead to improved solutions. Nevertheless, it may not be desirable to run the model every single time slot, as computation power is still costly and energy-intensive. Furthermore, each iteration requires an information exchange between households and the MGO, and not all iterations of the classical rolling horizon model may improve the solution equally (e.g. in the middle of the night, no improved PV forecasts nor observations of realized EV demand may be expected).

However, there exists a fundamental difference in the underlying reason for the PV and the EV improvements:

» Focusing on the PV improvements first, we notice that the improvement in the objective value stems from (a series) of improved and more accurate PV forecasts, which built up the PV uncertainty sets. As these forecasts are made for specific time slots, we need to react to these improved uncertainty sets before the corresponding time slot to be able to get any improvements in the objective value. Hence, the PV improvements are highly time-critical, also due to the assumption that the improvements get larger the closer the forecast is made w.r.t. its corresponding time slot. Therefore, the time slot when iterations are started has a large impact on the objective value.

» The EV improvements on the other hand stem from observations of realized uncertainty, in this case of the uncertain EV demand. Due to the working of robust optimization to ensure feasibility also for the worst case scenario, there is often a surplus of energy within the EVs, which can either be sold at the (intraday) market or which reduces the amount of energy bought in future time slots. This selling of a surplus of electricity is only a short-term improvement, which can be observed once toward the end of the time horizon, see also the analysis of Figure 5.4 in Section 5.4.2. However, in practice, there is no end to the time horizon, and therefore, the improvement due to the selling of the surplus does not play a role in the long-term perspective. In addition, the uncertain EV demand is realized within a buffer, namely the EV battery, and therefore, the algorithm can still react to it later on, as the surplus does not simply vanish from the battery. Due to the working of the day-ahead market, we assume to run the model at least once a day, and thereby will surely observe this surplus regularly. Therefore, the EV improvements are not time-critical and mainly independent of the time slots in which the iterations of a rolling horizon start.

Summarizing, we have two sources of improvements, one of which is time-critical and heavily depends on the starting time slots of the iterations, and another one, which is (nearly) independent of the starting time slots of the iterations. Hence, in the following, we focus only on the PV uncertainty to further improve the rolling horizon by a more intelligent choice of the starting time slots of the iterations of the rolling horizon.

5.5 Generalized Rolling Horizon Framework

As concluded in the previous section, there is still room for improvement as not all iterations of the classical rolling horizon model offer significant further information to the model. Hence, skipping these iterations is expected to yield the same or comparable results. Based on these insights, we develop the classical rolling horizon framework further, by allowing more flexibility in the starts of the iterations. To allow the more flexible starts of the iterations, we drop the parameter of the step size and replace it with the maximal number of iterations per time horizon. Thereby, we do not allow more iterations during the considered time horizon but allow a more flexible scheduling of the iterations. To decide when to start the iterations, we design a tailor-made scheduling tool, which uses structural knowledge of the uncertainty and robust optimization to identify promising starting time slots for the iterations of the rolling horizon. The scheduling tool is loosely based on the well-known knapsack problem and can be reduced to a longest k-arc path problem, which can be solved efficiently using dynamic programming. In the remainder of this chapter, we refer to the combined rolling horizon framework with the scheduling tool as the generalized rolling horizon. We then proceed with a short analysis of the proposed starting time slots and a comparison to the classical rolling horizon-based approach before discussing advantages and disadvantages.

5.5.1 Scheduling Tool

To allow for an easier adaption of this idea to other applications, we first introduce a base version of the problem, including the necessary parameters. In a second step, we provide an overview of the explicit parameter choices for the case of the energy management problem.

Input Parameter and Notation

To decide when to execute iterations of the rolling horizon, we consider the following input data:

» In applications of a rolling horizon framework, the considered time horizon of the problem is usually split up into a set of equidistant time slots. $\mathcal{T} = \{0, 1, \ldots, T\}$ denotes the set of time slots. As we consider an ongoing rolling horizon, we assume that an initial solution is given, which could be the solution of the last iteration of the previous time horizon. Within $\mathcal{T}$, let time slot 0 represent the time slot of this initial solution.

» $c \in \mathbb{R}_{\geq 0}^{|\mathcal{T}| \times |\mathcal{T}|}$ represents the information gain over time within the rolling horizon, whereby the parameter $c_{s,t}$ denotes the information gained when starting an iteration of the rolling horizon at time slot t, given that the previous iteration started at time slot $s < t$.

» $k \in \mathbb{N}_{>0}$ is a positive integer denoting the maximal number of iterations of the rolling horizon over the time horizon $\mathcal{T}$. This upper bound on the number of iterations may be imposed by various aspects, such as e.g., computational resources, limited (desired) communication, or other setting-dependent constraints.

» $\mathcal{M} = \{i_0, i_1, \dots, i_m\} \subset \mathcal{T}$ is a given set of time slots, which needs to be part of the set of selected time slots, where an iteration of the rolling horizon is executed. As time slot 0 corresponds to the initial solution, we assume that $0 = i_0 \in \mathcal{M}$. In general, $\mathcal{M}$ could represent certain time slots, in which decisions need to be communicated or submitted to markets or other internal or external entities within the considered setting.

Within the following, we first introduce the knapsack-based formulation, before relating it to a longest-path formulation, which we show can be efficiently solved via a dynamic programming approach. As both models are based on well-known combinatorial optimization problems, we stick to their usual notation. Figure 5.5 provides a mapping between the notation of the various models and the online scheduling algorithm.

rolling horizon	gained information	set of time slots	max. number of iterations	set of fixed iterations
knapsack	valuation	items	knapsack size	set of fixed items
longest path	length	nodes	max. path length	set of fixed nodes
online algorithm	contribution	time slots	max. number of iterations	set of fixed iterations
applied EMS	improved PV forecasts	time slots	max. number of iterations	day-ahead time slots

Figure 5.5: Overview and mapping between the used notation within the different models.

Knapsack Formulation

The general idea behind the knapsack formulation is that the items of the knapsack correspond to the potential starting time slots of iterations of the rolling horizon, while the valuation of an item corresponds to the additional information it can provide when starting an iteration in this time slot. In our setting, all items have a weight of one, while the knapsack size corresponds to the maximal number of iterations during the time horizon. This also implies that we have a topological ordering on the items of the knapsack problem, which directly follows from the structure of the time slots.

Let x_t, $t \in \mathcal{T}$, be a binary variable indicating whether to include item t into the knapsack or not. As the valuation of an item t depends on the choice of its predecessor s, let $y_{s,t}$, $s < t$, be an auxiliary binary variable to link the chosen items to their corresponding valuation. The objective is to maximize the value of the chosen items:

$$\max \sum_{s,t \in \mathcal{T}} c_{s,t} y_{s,t}. \tag{5.3}$$

The classical knapsack constraint, which limits the number of items to at most k, is

$$\sum_{t \in \mathcal{T}} x_t \leq k + 1. \tag{5.4}$$

Note that we use an upper limit of $k+1$, as item 0 is also included, but should not count as an iteration. To ensure that the items in $\mathcal{M}$ are chosen, we add constraints

$$x_t = 1 \quad \forall t \in \mathcal{M}. \tag{5.5}$$

The following constraints link the variables x_t with the auxiliary variables $y_{s,t}$ and thereby establish a connection to the valuations:

$$y_{s,t} \leq x_t \quad \forall s, t \in \mathcal{T}, \tag{5.6}$$

$$y_{s,t} \leq x_s \quad \forall s, t \in \mathcal{T}. \tag{5.7}$$

To ensure that only the valuations between neighboring items are counted, we need two types of constraints. The first constraint ensures that each item counts at most once as the beginning and at most once as the finishing item within the $y_{s,t}$ variables, which have a value of 1:

$$\sum_{s \in \mathcal{T}} y_{s,t} \leq 1 \quad \forall t \in \mathcal{T}, \tag{5.8}$$

$$\sum_{t \in \mathcal{T}} y_{s,t} \leq 1 \quad \forall t \in \mathcal{T}. \tag{5.9}$$

To ensure that only the valuations between neighboring chosen items are counted, we add the following constraints:

$$1 - x_t + y_{s,t} \geq y_{s,l} \quad \forall s, t, l \in \mathcal{T}, s < t < l. \tag{5.10}$$

If items $s < t < l$ are all taken, then $x_t = 1$. The above constraints then simplify to $y_{s,t} \geq y_{s,l}$, which together with constraint (5.9) ensures that $y_{s,l} = 0$ and the valuation $c_{s,l}$ does not add to the objective. If s is not taken, then all variables $y_{s,t}$ are automatically zero, and if t is not taken ($x_t = y_{s,t} = 0$), then the constraint simplifies to $1 \geq y_{s,l}$, which does not lead to any restrictions. Hence, the objective function (5.3), together with constraints (5.4)-(5.10) forms the knapsack problem.

Reduction to Graph-Based Problem

Analyzing constraints (5.8)-(5.10), it becomes obvious that the y variables actually have to form a path on some graph over $\mathcal{T}$. Constraints (5.8) and (5.9) ensure that there is at most one in-going and at most one out-going arc for each node $t \in \mathcal{T}$, while equation (5.10) ensures that only arcs between consecutive time slots may be taken. Coupled with the objective (5.3) and the non-negativity of the c values, an optimal solution corresponds to a path of at most k arcs. Summarizing, the above knapsack problem can be reduced to a longest path problem with at most k arcs, visiting all nodes in $\mathcal{M}$, on a directed graph, spanned on the set of time slots $\mathcal{T}$.

To formalize, the graph is a complete directed acyclic graph $\mathcal{G} = (\mathcal{V}, \mathcal{A}, c)$, in which the node set $\mathcal{V}$ corresponds to the time horizon $\mathcal{T}$, enlarged by an artificial node $T+1$. The set of directed arcs $\mathcal{A}$ consists of arcs (s,t) for all pairs $s,t \in \mathcal{V}$, $s < t$, and the arc length c is given by the information gains c. Furthermore, the natural ordering of the time slots corresponds to the unique topological ordering of the nodes of the graph. For completeness, the arc length for the arcs going into the artificial node $T+1$ is given by $c_{s,T+1} = 0$. The knapsack problem of finding an optimal solution with at most k items, using all items in $\mathcal{M}$ now translates into the problem of finding a $0-(T+1)$-path of at most $k+1$ arcs, which visits all nodes in $\mathcal{M}$ and maximizes the length along this path.

Due to the topological ordering of the directed acyclic graph $\mathcal{G}$, this problem can be solved using two different *dynamic programming* approaches in $\mathcal{O}(T^2 k)$ time. In a first step, we compute for $j = 0, \dots, m$ the longest paths between nodes $i_j, i_{j+1} \in \mathcal{M}$ with exactly $h \in \{1, \dots, \min(k+1, i_{j+1} - i_j)\}$ arcs, where $i_{m+1} = T+1$. This can be done in time $\mathcal{O}(T_i^2 k)$ for each pair i_j and i_{j+1}, whereby $T_i = i_{j+1} - i_j$. Summing up over all pair of nodes i_j, i_{j+1}, we have a total complexity of $\sum \mathcal{O}(T_i^2 k) \leq \mathcal{O}(T^2 k)$, as $\sum T_i = T$. In a second step, we reduce the original graph to the node set $\mathcal{M} \cup \{T+1\}$ and use the previously computed longest paths with h arcs between neighboring nodes. By a second dynamic programming approach, the longest path from node 0 to node $T+1$ using at most $k+1$ arcs can be calculated in a straightforward way in an iterative fashion. The running time of this second dynamic program is $\mathcal{O}(mk^2)$, leading to an overall complexity of $\mathcal{O}(T^2 k)$, as $T > k > m$, see Appendix 5.8 for further details.

Parameter Choices for the Energy Operation Problem Under Uncertainty

Assuming average contributions, we use historical knowledge of how the uncertainty sets for a given time slot t shrink over time, as assumed by equations (5.1) and (5.2). Let $\beta^{PV}_{l,t} \in [0,1]$ be the reduction factor of the PV uncertainty interval for time slot l, expressing an improved forecast at time t compared to the initial (long-term) forecast at time 0. Then the average improvement of the lower limit of the PV uncertainty interval for time slot l made at time slot t compared to the initial uncertainty set derived at time slot 0 can be expressed as $p_l^{PV}\alpha_l^{PV}\beta_{l,t}^{PV}$. Hereby, $2p_l^{PV}\alpha_l^{PV}$ would correspond to the length of the uncertainty set derived at time slot 0, however, we are only interested in an improvement of the lower limit of the uncertainty set, hence using $p_l^{PV}\alpha_l^{PV}$. As at time slot t, we do not only receive an improved forecast for the same time slot, but for all future time slots, we have to add this expected improvement over all future time slots. Hence, the average or expected improvement for starting an iteration at time slot t in relation to the last start at time slot s is given by

$$c_{s,t} = \sum_{l=t}^{|\mathcal{T}|} p_l^{PV}\alpha_l^{PV}\left(\beta_{l,t}^{PV} - \beta_{l,s}^{PV}\right). \tag{5.11}$$

This improvement can then be seen as the additional available PV generation compared to time slot s. These values are used as the directed arc lengths for the longest path model.

5.5.2 Analysis of the Scheduling Tool and its Starting Time Slots

In the following, we analyze the scheduling tool regarding its choice of starting times for the iterations of the rolling horizon and compare it to the classical rolling horizon scheme introduced in Section 5.4. We use the same data and simulation setup as in the previous section but restrict the time horizon to one day.

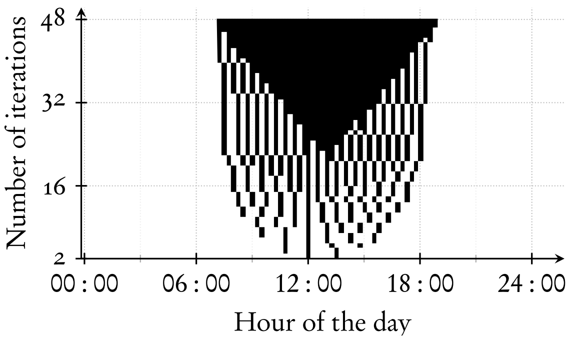


Figure 5.6: Selected starting time slots (in black) of the dynamic scheduling tool depending on the chosen number of iterations (y-axis).

Figure 5.6 shows the starting time slots proposed by the scheduling tool for one day for different numbers of iterations. It can be seen that starting time slots during the day are preferred to time slots throughout the night when no PV generation is present. In addition, it can be observed that even with very few starting time slots, the knapsack problem spreads these slots evenly over the majority of the time window of the PV production. As the number of starting time slots increases, the gaps between the chosen starting time slots decrease, and time slots early in the morning or late in the evening are included. For 48 starting time slots, which correspond to a step size of 2, every time slot with PV production is included.

In comparison to the classical rolling horizon, the starting time slots of the generalized rolling horizon are much more clustered around time slots offering a potential improvement in PV forecasts. The classical rolling horizon on the other hand, equally spreads its starting time slots throughout all 24 hours of the day. Thereby, roughly half of its iterations are scheduled during the night, where no improved PV forecasts can be accessed.

5.5.3 Comparison to the Classical Rolling Horizon-Based Approach

In the following, we directly compare the classical and the generalized rolling horizon models with each other and thereby try to confirm the theoretical analysis. We test the two models for various step sizes and the corresponding number of iterations. Note that each step size implies a fixed number of iterations throughout the time horizon of 3 days, and both parameters are used interchangeably. The considered step sizes are 96, 48, 24, 16, 12, 8, 4, and 2 with each step size being tested for all three uncertainty scenarios A, B, and C (see Table 5.1). In addition to the average cost, we also use the average PV usage as a measure of how efficiently the improved starting times of the generalized rolling horizon can capture the time-dependent PV uncertainty sets. This choice is based on the insights gained during the analysis of Figure 5.4, which indicates that the dynamic PV uncertainty sets are the driving factor behind the observed improvements of the rolling horizon models. The achieved results for the three scenarios are given in Tables 5.4, 5.5 and 5.6.

Table 5.4: Comparison of classical and dynamic RH, Scenario A

Step size/ iterations per day	classical RH	generalized RH	rel. improvement
$\lvert\mathcal{T}\rvert$ / 0	-10.8099	-	-
96 / 1	-10.1937	-10.1937	0.0%
48 / 2	-10.5697	-10.6399	0.7%
24 / 4	-10.6338	-10.9147	2.6%
16 / 6	-10.7521	-11.1579	3.8%
12 / 8	-10.9201	-11.3025	3.5%
8 / 12	-11.0491	-11.5721	4.7%
4 / 24	-11.5565	-11.9146	3.1%
2 / 48	-11.9363	-12.1420	1.7%

Starting with scenario A (see Table 5.4), we notice that both rolling horizon models need a few iterations (step size 12 for the classical rolling horizon, respectively 24 for the generalized version) to surpass the fully static robust model, denoted by a step size of $\mathcal{T}$. Due to the small uncertainty sets within this scenario, the information gains of the rolling horizon schemes are relatively small compared to the advantage of considering the complete time horizon at once. Hence, it needs some iterations to build up the required information gain to surpass the advantage of considering the complete time horizon.

Focusing on the comparison between the classical and the generalized rolling horizon models, we observe that the improvement of the generalized model first increases with additional iterations, but then decreases again as soon as the step size gets smaller. For small step sizes, the classical rolling horizon model already covers most of the important starting time slots over the day, and it can therefore make use of most of the additional information of the dynamic PV uncertainty sets. Note that for a step size of 1, both models can start an iteration at every time slot, resulting in the same solution.

Table 5.5: Comparison of classical and generalized RH, Scenario B

Step size/ iterations per day	classical RH	generalized RH	rel. improv.
$\|\mathcal{T}\|$ / 0	4.6367	-	-
96 / 1	4.9705	4.9705	0.0%
48 / 2	4.3666	3.8631	11.5%
24 / 4	4.2409	3.2276	23.9%
16 / 6	3.9931	2.7623	31.1%
12 / 8	3.6239	2.4049	33.6%
8 / 12	3.3367	1.8427	44.8%
4 / 24	1.9621	0.9726	50.4%
2 / 48	0.9762	0.4192	57.1%

For the standard scenario B, both rolling horizon models outperform the fully static robust model for step sizes smaller or equal than 48 (see Table 5.5). When comparing the two rolling horizon schemes with each other, the structure of the relative improvements differs from the previous case. Instead of having a peak at a step size of 8, followed by a decrease, the relative improvements steadily increase further. This can be explained by the fact that the values tend towards 0 and by that already small improvements can lead to large relative deviations. If instead, the absolute values, as shown in Figure 5.7, are analyzed, the same structure of an increase in improvements up to a step size of 8, followed by a decrease in improvements can be observed.

In scenario C, both rolling horizon models outperform the fully static robust model already for a step size of 96 (see Table 5.6). Hence, using the updated dynamic uncertainty sets only once a day already provides enough additional information to surpass the advantage of considering the whole time horizon. The results for scenario C support the previous analysis, in that up to a step size of 8, the improvements of the generalized model steadily increase. Only for step

Table 5.6: Comparison of classical and generalized RH, Scenario C

Step size/ iterations per day	classical RH	generalized RH	rel. improv.
$\lvert\mathcal{T}\rvert$ / 0	22.6208	-	-
96 / 1	20.3452	20.3452	0.0%
48 / 2	19.2826	18.9569	1.7%
24 / 4	19.0863	18.2586	4.3%
16 / 6	18.8243	17.6324	6.3%
12 / 8	18.4443	17.1576	7.0%
8 / 12	18.0163	16.5639	9.1%
4 / 24	16.5472	15.5044	6.3%
2 / 48	15.4005	14.8201	3.8%

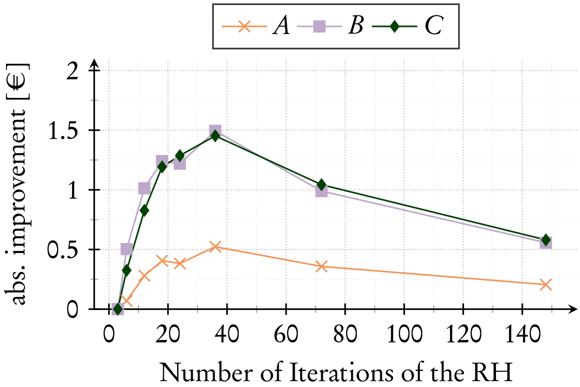


Figure 5.7: Absolute improvements in the objective value between classical and generalized RH for different step sizes and uncertainty scenarios.

sizes 2 and 4, the improvements are getting smaller, due to the better placement of iterations of the classical rolling horizon model.

For the local PV usage, Figure 5.8 displays the relative improvements of the generalized rolling horizon models over the classical ones, and Figure 5.9 displays the PV usage percentages. As can be seen in Figure 5.8, the generalized rolling horizon models outperform the classical ones throughout all step sizes, and the overall shape of the relative improvements are rather similar to the (absolute) improvements in objective value, as displayed in Figure 5.7. This aligns well with our conclusion in Section 5.4.3, which highlighted the impact of the dynamic uncertainty sets on the objective value. Furthermore, the tailor-made scheduling tool, introduced in Section 5.5.1, works as intended and significantly increases the PV usage through clever scheduling of the starting time slots of the rolling horizon (see also Figure 5.9). In addition, the values displayed in Figure 5.9 also align well with the dynamic uncertainty sets of the PV generation for each of the three uncertainty scenarios A, B, and C. While the fully static model only

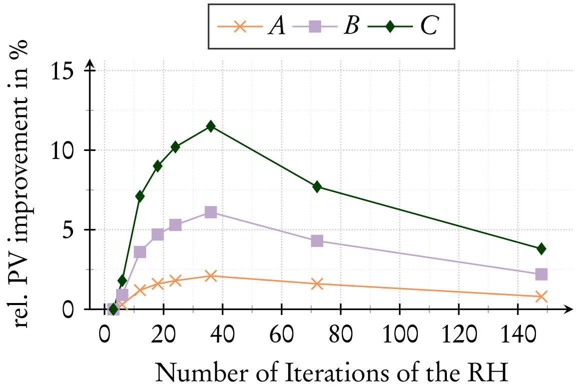


Figure 5.8: Relative PV usage improvements between classical and generalized RH for different step sizes and different uncertainty scenarios.

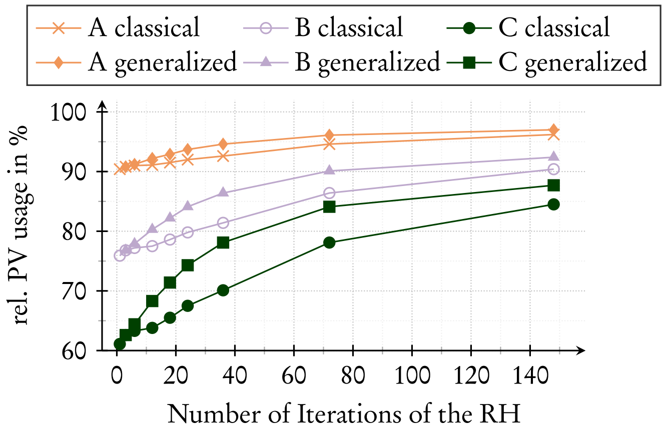


Figure 5.9: Absolute PV usage for different uncertainty configurations and rolling horizon models.

uses roughly $1-\alpha^{PV}$ of the realized PV generation, which fully aligns with the robust approach, both rolling horizon models quickly improve upon this usage.

5.5.4 Discussion

Summarizing the above analysis, we notice that the generalized rolling horizon model better coordinates the iterations of the rolling horizon framework and thereby improves the handling of the considered uncertainty. The generalized model allows to derive tailor-made starting times, which are able to capture the time-critical uncertainty of the PV generation. As a consequence, the generalized rolling horizon model can achieve similar or even better solutions than the classical version with less than half the number of iterations (see Tables 5.4 - 5.6). An advantage, that it shares with the classical rolling horizon approach is that the time slots, in which the underlying robust energy management problem needs to be solved, are known in advance, which makes the planning on possibly shared hardware easier.

However, it should be noted that the early choice of the starting time slots also leads to a disadvantage, which directly follows from the offline nature of the decision-making process. The decision when to start the iterations of the rolling horizon is already made at the start of the considered time horizon, and therefore it does not allow to adapt its starting time slots to particularly good (or bad) forecasts or observations of uncertainty. Specifically, given the nature of the considered problem, it is of high importance to be able to react to extreme or unusual events. A second problem is the assumption of average realizations of future uncertainty to compute the starting time slots. This may be a reasonable choice if the expectation of the uncertainty realization is close to the average. However, for a skewed underlying uncertainty distribution, this could considerably affect the outcome of the optimized starting time slots and lead to worse results.

5.6 Online Generalized Rolling Horizon

Based on the above considerations of the generalized rolling horizon model, we propose an online version of the generalized rolling horizon framework, which improves upon both of the above-mentioned disadvantages. Instead of deciding upon the starting time slots in advance, the online rolling horizon framework decides on the fly whether to start an iteration or not. Thereby, it is able to react to updated forecasts or observed realizations of uncertainty and can make better decisions regarding the starting time slots of the iterations. Instead of using the previously introduced path problem to identify the starting time slots, we use it to compute the average or expected improvement in PV usage. We then use this value as the threshold for an online threshold algorithm, which is run every time slot to decide whether or not to start an iteration of the rolling horizon. The online threshold algorithm is inspired by algorithms with a constant competitive ratio for various online problems, such as the online knapsack, multi-secretary, or prophet inequality problem. In addition, it makes use of the main principles of robust optimization and is thereby able to react to extremely good or bad forecasts or realizations of uncertainty.

5.6.1 Overview of Online Algorithms

As mentioned, an online approach to schedule the starting time slots of a rolling horizon may have several benefits over an offline scheduling approach. To gain insights into the working of online algorithms, a review of solution approaches for various online combinatorial optimization problems is given, which are based on a similar online problem structure as the online scheduling of the iterations of a rolling horizon in this study. Note that the reviewed literature analyzes the online problems from a theoretical perspective, where the main goals are to derive (constant) competitive online algorithms. Although this theoretical focus differs from the rather practical application in our study, high-level concepts and ideas can still be applied to our problem.

Online optimization has been an important research direction in the area of (combinatorial) optimization for many years now. Online problems, in which items arrive one by one, and for each item it has to be decided irrevocably whether to keep or discard it, can be found in online versions of the knapsack problem, the (multi-)secretary problem, resource assignment problems, or prophet inequality problems. Next to some negative results on the competitiveness of online algorithms for some of these problems [170], promising online algorithms have been developed under some (mild) assumptions. These assumptions range from knowledge of distributions or ranges of values for certain item parameters [170, 240, 276] to the order in which items may arrive [8, 159]. Independent of these different assumptions, many of the proposed competitive online algorithms are based on the same high-level solution approach with small differences in specific elements of the algorithms, often reflecting the various assumptions.

In [8], the values of the items are drawn independently from known distributions and the items arrive in a uniformly random order. The focus is to derive a static threshold, such that the values of the first k items with values exceeding this threshold are maximized in expectation. The decision rule is therefore based on two parameters, namely the value of the items, as well as the static threshold.

In [268], the used threshold is not static, but a linearly increasing function of the utilization rate of the knapsack (in multiple dimensions). In addition, the weight of the item is also included in the threshold. Again, the value of an item gets known as soon as the item arrives and an irrevocable decision regarding the usage of this item has to be made. Furthermore, a second online algorithm is proposed, which admits an exponential threshold function. This threshold function is again increasing in the utilization rate of the knapsack and also includes the weight as a factor. In comparison to the linear threshold function, this exponential threshold is more conservative in admitting items and prefers to reserve available space for future high-value items. Further exponential threshold functions depending on the utilization of the knapsack are presented in [239, 240, 274, 276] among others. In addition to the utilization rate of the knapsack, in [274, 276] upper and in [239, 274, 276] lower limits on the value to weight ratio of the items or upper limits on the item size [240] are assumed to be known.

Instead of using the knapsack utilization rates as the base for the thresholds, another approach for a threshold is to first observe some of the arrivals and then use the observed data to derive a threshold [12, 38, 92, 122, 159, 240]. This threshold is based on the values of the already observed items, similar to solution approaches for the classical secretary problem, in which the algorithm first observes a certain fraction of the online input, and the largest observed value is then used as the threshold for the remaining online input (see [65]). In [122] and in [159], the set of values, which should first be observed is referred to as the *history set H*, and considered to be part of the input and not of the actual online problem, in which decisions are made. In case H is small, the first items in the online phase are still only observed to gain additional information, similar to [65]. In [92], various threshold-based online algorithms are proposed. Some directly rely on the original algorithm for the classical secretary problem [65], while others randomly select the number of items to first observe. In [12] on the other hand, the set of items is split up into L subsets, and after each round, the threshold is updated based on the solutions of the previous subset of items. A similar approach is used in [38], in which some of the items arrive randomly within the time horizon $[0,1]$, and the split into subsets is done on the time horizon with updated thresholds for each interval.

A class of online problems, that closely resembles the considered online scheduling problem of a rolling horizon framework, are prophet inequality problems. In particular combinatorial prophet inequality problems, first introduced in [211] and improved in [45], are built upon a very similar structure. In these problems, the decision maker is faced with a sequence of n items, drawn from n known (discrete) distributions. At each iteration, an item is drawn from the corresponding distribution and presented to the decision maker, who must decide irrevocably whether to take the item or not, subject to matroid constraints. The goal is to maximize a submodular function f over the set of chosen items. There are two main differences to the considered online scheduling problem of a rolling horizon. The first is the discrete nature of the underlying distributions. This difference may be overcome by approximating the continuous probability distributions by means of discrete distributions without losing too much information. The second difference lies within the knowledge of future distributions of the combinatorial prophet inequality problem. In our setting, we do not know the probability distributions, and therefore we are not able to directly apply the proposed algorithms to our case. In contrast to the previously considered literature, the algorithm is not based on an online threshold algorithm but is heavily dependent on *Online Contention Resolution Schemes*, which is a rounding technique for online optimization problems [78].

5.6.2 Online Threshold Algorithms

Summarizing the above-presented literature, the key similarity of most of the reviewed literature is the structure of how to decide whether to take item t or not. This structure can be generalized and compressed to the following rather simple equation:

$$c_t \geq f(t,x)\tau, \tag{5.12}$$

where c_t is the value or contribution of item t, $f(t,x)$ is a factor, which may depend on time slot t and further information x, such as how many items have already been taken or proposed, and τ is a threshold. Note that compared to the considered literature, the threshold is split into a threshold and a factor. If the value of the item exceeds the (factored) threshold, then the item is taken. Translating this simple decision process into the setting of an online scheduling problem for a rolling horizon, τ still may remain a threshold to be determined, while $f(t,x)$ may represent the possible dynamic nature of the threshold. On the other hand, the value c_t of the current time slot t may translate to the additional information, which the algorithm has access to in time slot t compared to the last starting time slot. In contrast to the reviewed online literature, in our case, we are not simply given such a value c_t but have to compute it.

Based on the principle of equation (5.12) as well as the insights from the online literature, we identify three main lines of online algorithms, each with a distinct difference in either the value of a time slot or the threshold:

» *Average-Realizations (AR) approach*: Based on the longest path model introduced in Section 5.5 to determine optimal starting time slots, we define the individual contributions of each of the proposed optimal starting time slots. We use average realizations or predictions of the uncertainty as parameters for the path problem. After computing the individual contributions, we apply some function g on the vector of contributions and use the corresponding result as the threshold. The contribution of the current time slot t is computed based on the same type of data, but instead of using average realizations and forecasts, we can now use the actually observed realizations and current forecasts.

» *Historical-Realizations (HR) approach*: Instead of using the longest path model with average realizations as the values, we may also use historical data to find optimal starting time slots for past days in hindsight. This historical data can be seen as samples from the same underlying, unknown probability distribution, as used in prophet inequality problems, or as the set of items that should first be observed, as done in several online knapsack or secretary problems. Based on the chosen starting time slots, the individual contributions can easily be computed and used as the threshold. The contribution of time slot t is again computed based on actual observations and updated forecasts.

» *Partial-Realizations (PR) approach*: Instead of using the longest path model only once to compute individual contributions of optimal starting time slots, the model can also be used in an iterative online fashion. For each time slot, the model is run with updated real-time data, such as current forecasts and observed realizations of the previous time slots $s < t$. After solving the path problem with updated information, the decision of whether to start an iteration during the current time slot t depends on the current solution. If node t is part of this path, an iteration of the rolling horizon is started, else we repeat the process for the next time slot $t+1$.

In the following subsections, we focus on how to determine the contribution, threshold, and factor for time slot t for each of the three main lines, given that the last starting time slot of the rolling horizon was a time slot $t_l < t$.

Contribution

In contrast to the simply observable value of an arriving item within an online knapsack, secretary, or prophet inequality problem, in our case, the value for the time slots needs to be computed. Hence, in the following, we refer to this value as the contribution of the current time slot.

» For the AR approach, we need to compute the contribution based on the differences in available information between the current time slot t and the last starting time slot t_l. Depending on the application, the available information can either be in the form of updated forecasts or observed realizations of uncertainty since the last start.

» The contribution for the HR approach is the same as for the AR approach.

» The PR approach uses the optimal solution of the path model with updated values to derive the contribution. If the current time slot t is part of the optimal path, we define the contribution as one, and if it is not, we simply set the contribution to zero.

Threshold

All three main approaches (AR, HR, PR) derive their thresholds based on different data sets. While the AR approach is based on average values, the HR approach uses historical data to compute its threshold. The PR approach already uses its data within the computation of the contribution and can therefore make use of a very simple threshold. Within the following discussion of these thresholds, some (high-level) ideas from the reviewed literature can be identified.

» The threshold for the AR approach is based on the optimal solution of the path model with average values as input parameters. Instead of directly using the nodes within the optimal path as fixed starting time slots of the iterations of the rolling horizon, as done in Section 5.5, the AR approach instead uses the optimal objective value to compute its threshold. The objective value can be split up into the individual lengths of the arcs in the optimal path. As the vector of those values cannot directly be used as the online threshold, which consists of a single value, we need to apply some function on the vector to project it to a single number. Instead of using either the maximal, minimal, or average value as the threshold, we test and analyze the impact of different percentiles as the threshold.

» The threshold for the HR approach is also based on the lengths of the arcs of the optimal path. Instead of using average data for the values as done for the AR approach, the HR approach is based on historical data. We assume to have access to N_{HR} such historical data sets, which represent 'similar' conditions as predicted for the current time horizon. This historical data is then used to compute optimal solutions in hindsight. The individual contributions of each of the N_{HR} optimal paths are then grouped together and the percentile function is applied to generate one single value based on the vector of individual contributions.

» The threshold for the PR approach is relatively simple compared to the previous two approaches. As the contribution is either 0 or 1, represented by the optimal path, we simply set the threshold to 1.

Factor

Based on the literature review of comparable online combinatorial optimization problems, most approaches use some form of dynamically changing threshold, often based on the utilization rate. The previously introduced thresholds do not reflect this dynamic nature yet. Therefore, we have introduced the factor $f(t,x)$ in equation (5.12) to account for that. In addition, insights into the structure of the underlying uncertainty as well as the shape of the contributions may be used to design 'tailor-made' factor functions $f(t,x)$. These factors $f(t,x)$ can be applied to the thresholds of the AR and HR approaches. Based on insights gained during the testing, the values of the factor functions should be centered around 1 to not change the threshold too much. To keep the functions general, we introduce a lower bound L and an upper bound U for the functions, whereby we assume $L < 1 < U$. The considered parameterized factor functions are then:

1. *Constant*: A constant factor $f(t,x) = 1$, leaving the 'pure' threshold, similar to ideas in secretary or prophet inequality problems (see e.g., [8, 65]).
2. *Step-wise constant*: To discourage long periods without starting any iteration, we introduce a step-wise constant factor. This factor starts with a constant factor of 1 but decreases to a value of L in case the time since the last starting time slot t_l exceeds a certain setting-specific threshold R. This decrease should encourage to start another iteration, as the factored threshold also decreases, making it easier to start another iteration. Concrete, we use

$$f(t,x) = \begin{cases} 1 & \text{if } t - t_l \leq R \\ L & \text{if } t - t_l > R \end{cases}. \tag{5.13}$$

3. *Linearly increasing*: Inspired by the linear threshold function presented in [268], the following factor is considered:

$$f(t,x) = (U - L)x + L. \tag{5.14}$$

Note that this factor is not based on the time slot t, but rather on the iteration usage rate x, which represents the percentage of already used iterations during the time horizon. The main idea behind an increasing factor depending on the number of already started iterations is that in the beginning, it should be easier to start an iteration, but the more iterations have already started, the more difficult it should get and the 'pickier' the algorithm should be.

4. *Exponentially increasing*: Much of the reviewed literature is based on an exponential threshold of some form (see e.g., [240, 276] among others). They are based on the utilization rate, a concept that we also use within this factor function. In contrast to exponential thresholds, which admit any item up to a given utilization rate (see e.g., [276]) we slightly lower the threshold in the beginning and then directly increase it. This leads to the following factor function

$$f(x) = a\exp(cx) + b, \tag{5.15}$$

where a, b and c are chosen such that $f(0) = L$ and $f(1) = U$. In Figure 5.10, c is chosen to be 2.5, while $L = 0.8$ and $U = 1.2$.

5. *Quadratically increasing and decreasing*: The idea of starting with a lower threshold and then making it more difficult to start new iterations, as done for the linear and the exponential factors, has been inspired by the reviewed theoretical work on online-competitive algorithms. In practice, on the other hand, this increasing factor leads to situations, in which not all of the possible iterations are used, which leaves potential unused. To counter this, we let the quadratic factor not continue to increase with the utilization rate x, but decrease it again for $x > 0.5$. We define the function as follows:

$$f(x) = a(x - 0.5)^2 + b, \tag{5.16}$$

where a and b are again chosen such that $f(0) = f(1) = L$ and $f(0.5) = U$.

6. *Factored threshold based on [276]*: Next to concepts from literature, we may also directly use a (slightly modified) version of the threshold function presented in [276]. However, as the assumption of a strictly positive upper and lower limit on the value does not hold in this study, we simply use the minimal and maximal contribution values of the HR knapsack problem as the lower and upper limit.

Parameter Choices for the Energy Management Problem Under Uncertainty

Determining the values and contributions needed for the online scheduling framework for this robust energy management problem is based on the improvements in PV forecast over time. The conservative approach of robust optimization enforces that the obtained solution is feasible w.r.t. all possible realizations of the uncertain parameter. In the case of the uncertain PV generation, this translates into using at most the lower limit of the PV uncertainty interval.

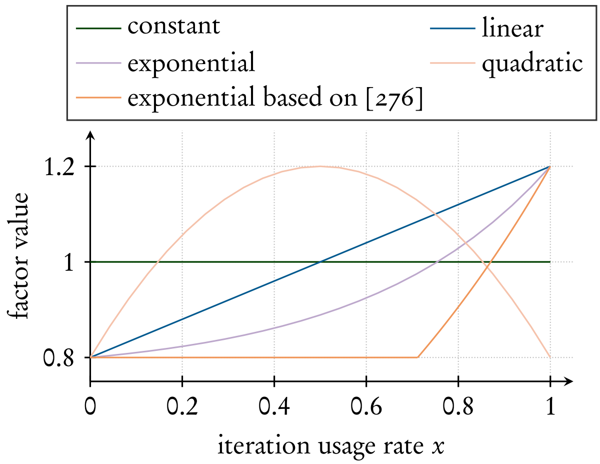


Figure 5.10: Plot of the different factors, given a lower bound of $L = 0.8$ and an upper bound of $U = 1.2$.

With each iteration, we get access to updated forecasts, and thereby also to (improved) lower limits of the PV uncertainty intervals. For the three considered different online scheduling algorithms, we have to estimate how much this lower limit will improve. This results in the following values and parameters:

» *AR approach*: We use the same assumption of average realizations as for the offline approach in Section 5.5, and can therefore use the same values as defined by Equation 5.11. In addition, we also need to compute the contribution of the current time slot t. In contrast to the assumption of average realizations for the information gains, we can use the current data and forecasts of time slot t and compute the improvements over the forecasts made at the last starting time slot t_l, resulting in

$$\tilde{c}_t = \sum_{s=t}^{\mathcal{T}} (p^{PV}_{t_l,s}(1-\alpha^{PV}_{t_l,s}) - p^{PV}_{t,s}(1-\alpha^{PV}_{t,s})), \tag{5.17}$$

as the contribution of the current time slot t.

» *HR approach*: We translate each of the given data samples into the longest path problem and thereby determine the optimal starting time slots of the iterations in hindsight. Given that, for each data sample, we know all historical PV forecasts, we compute the value $c_{s,t}$ for time slots $s < t \in \mathcal{T}$ by

$$c_{s,t} = \sum_{l=t}^{|\mathcal{T}|} \left(p^{PV}_{l,t}(1-\alpha^{PV}_{l,t}) - p^{PV}_{l,s}(1-\alpha^{PV}_{l,s})\right). \tag{5.18}$$

For a fixed time slot $l > t$, this can be seen as the improvement in the lower bound of the uncertainty interval of the PV production given the new starting time slot t over the previous prediction made at time slot s.

Remind that for the HR approach, the same threshold (5.17) as for the AR approach is used.

» *PR approach*: For the current time slot t, we combine the data of the average realizations with observations of the past. Let t_l again be the last realized starting time slot. Then, we have four different cases:

1. For arc (t_l, t), we simply use the predicted forecasts, and subtract the lower limits of the predicted PV uncertainty intervals:

$$c_{t_l,t} = \sum_{k=t}^{|\mathcal{T}|} \left(p_{k,t}^{PV}(1-\alpha_{k,t}^{PV}) - p_{k,t_l}^{PV}(1-\alpha_{k,t_l}^{PV}) \right). \tag{5.19}$$

   Due to constraint (5.1), the length of the arc (t_l, t) is always positive.

2. For arcs (t_l, l) with $l > t$, we again apply the idea of average reductions for future forecasts, while for time slot t_l, we can simply use the lower limits of the predicted PV uncertainty intervals. Hence, we have

$$c_{t_l,l} = \sum_{k=l}^{|\mathcal{T}|} \left(p_{k,t}^{PV}(1-\alpha_{k,t}^{PV} + \alpha_{k,t}^{PV}(\beta_{k,l}^{PV} - \beta_{k,t}^{PV})) - p_{k,t_l}^{PV}(1-\alpha_{k,t_l}^{PV}) \right), \tag{5.20}$$

   where the $p_{k,t}^{PV}(1-\alpha_{k,t}^{PV} + \alpha_{k,t}^{PV}(\beta_{k,l}^{PV} - \beta_{k,t}^{PV}))$ corresponds to the estimated lower limit of the PV uncertainty interval for time slot k, made at time slot l. Note that instead of using the long-term forecast made at time 0 as the basis for the improvement factors β, we use the most recent forecast from time slot t, which may already improve upon the forecast made at time slot 0. To account for that, we subtract the improvement factor $\beta_{k,t}^{PV}$ at time t, resulting in an updated improvement factor of $(\beta_{k,l}^{PV} - \beta_{k,t}^{PV})$. Hence, the lower limit of the PV uncertainty interval is based on the most recent lower limit estimation from time slot t, but adjusted for the average reduction factor. Using equation (5.1) and $0 \leq \beta_{k,t} < \beta_{k,l} \leq 1$, we have $c_{t_l,l} \geq 0$ for $l > t$.

3. For arcs (t, l) with $t < l$, we use the current prediction of time slot t and assume average realizations for future time slots

$$\begin{aligned} c_{t,l} &= \sum_{k=l}^{|\mathcal{T}|} \left(p_{k,t}^{PV}(1-\alpha_{k,t}^{PV} + \alpha_{k,t}^{PV}(\beta_{k,l}^{PV} - \beta_{k,t}^{PV})) - p_{k,t}^{PV}(1-\alpha_{k,t}^{PV}) \right) \\ &= \sum_{k=l}^{|\mathcal{T}|} \left(p_{k,t}^{PV}\alpha_{k,t}^{PV}(\beta_{k,l}^{PV} - \beta_{k,t}^{PV}) \right). \end{aligned} \tag{5.21}$$

4. For the remaining arcs (s, l), with $t < s < l$, we again assume the average realizations of the AR approach. That is, we use the current forecast at time slot t for future time slots k to compute how large the improvement of starting an iteration at time slot l is over time slot s. Hence, for time slots $t \leq s < l$ we have

$$c_{s,l} = \sum_{k=l}^{|\mathcal{T}|} p_{k,t}^{PV} \alpha_{k,t}^{PV} (\beta_{k,l}^{PV} - \beta_{k,s}^{PV}). \tag{5.22}$$

For all three approaches, let $\mathcal{M}$ be defined as the set of time slots, in which the decisions regarding the day-ahead market need to be submitted. Within this setting, these time slots are 12:00 every day.

5.6.3 Numerical Analysis of Online Threshold Algorithms

In this section, we focus on the analysis of the online threshold algorithms without the underlying robust energy management approach. We first test the impact of the threshold on the outcome of the online threshold algorithms, before analyzing the impact of the various individual parameter choices, such as the percentiles, the factor, or the different approaches. We first evaluate the results w.r.t. the objective value, that is the additional PV generation, before also shortly analyzing the number of used iterations. The following simulations are based on the same microgrid and household setting as used in the previous sections.

In contrast to Sections 5.3, 5.4 and 5.5, we extend the evaluation of the algorithm by two additional uncertainty probability distributions. While the usage of a uniform distribution, as done in the previous sections, is common in the context of robust optimization, in practice, error realizations do not always follow a uniform distribution. A very popular choice is the normal distribution (see e.g., [243, 270, 278]). We use a truncated normal distribution on the interval $[-1, 1]$ with mean 0 and standard deviation 0.4 to model the realizations for the PV uncertainty. We stick to the uniform distribution for the remaining uncertain parameters.

To also be able to analyze the performance of the various approaches under a non-zero mean error distribution, we also consider a truncated normal distribution with a shifted mean for the PV generation. Note, that the term non-zero mean does not imply that the forecasts of PV are off, but that the uncertainty is asymmetrically distributed around the predicted value. This may reflect that forecasting algorithms are able to predict the PV generation quite well if there are no clouds, but if there are a few clouds, which may block direct irradiation for short time periods, this will lead to larger (negative) deviations from the predicted value. Concisely, the uncertain PV generation is assumed to be given by a shifted normal distribution with a mean of 0.6 and a standard deviation of 0.4.

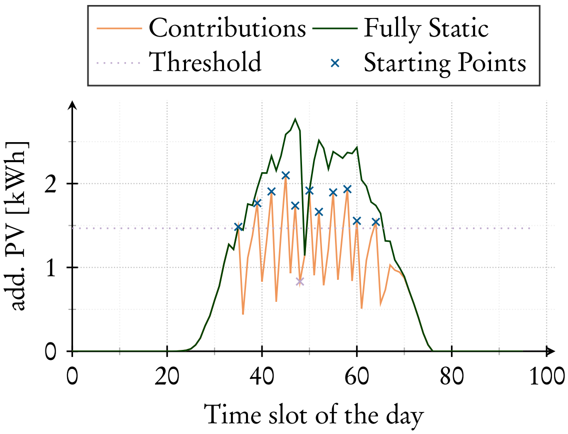


Figure 5.11: Contributions per time slot for online approach and fully static approach (solves the model only once).

Threshold

First, we focus on the impact of the threshold on the outcome of a basic online threshold algorithm with a constant threshold. We do not yet analyze the impact of the various parameters on the results of the algorithms but rather show how the online threshold algorithm works and how we can evaluate and compare its performance.

We start with a visual representation of the achieved results of the constant threshold-based online algorithm. Figure 5.11 displays the development of the contribution per time slot (see Equation 5.17), for one day based on a constant threshold. The individual contribution represents the additional PV generation, which can be used due to improved PV forecasts compared to the start of the last iteration. The figure also shows the used threshold as well as the chosen starting time slots. As can be seen, the algorithm starts an iteration whenever it exceeds the threshold. The iteration at time slot 48 is part of the set $\mathcal{M}$ and therefore ignores the threshold. Hence, the online algorithm works as intended. However, this may change if the threshold takes more extreme values. Figure 5.12 shows that if the threshold is too low, all iterations are used but are distributed very early during the day, whereas for a higher threshold, the starting time slots are distributed more evenly during the day, but do not use all possible iterations. As iterations starting very early or late during the day are likely to achieve smaller contributions, the choice of the threshold seems to be of great importance to achieve a well-balanced solution, in which (nearly) all iterations are used, but are also well spread among the time horizon.

Next to the visual analysis of the starting time slots, we can calculate the objective value of the online algorithms, given by the sum of collected contributions. The

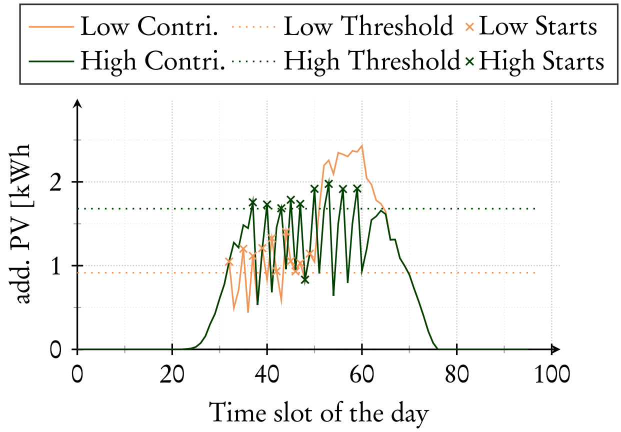


Figure 5.12: Contributions per time slot for online approach with a low and a high constant threshold.

resulting objective values for the three scenarios in Figures 5.11 and 5.12, confirm the initial intuition. While the threshold displayed in Figure 5.11 has an objective value of 20.333 kWh, the thresholds from Figure 5.12 only achieve an objective of 13.218 kWh (low), respectively 17.256 kWh (high). Hence, even a small change in the threshold can lead to a large change in the objective value.

The above comparison gives some insights into which threshold performs better, but it does not indicate how well the best threshold might perform. For this, we may use an upper bound on the objective value. Within the area of online (combinatorial) optimization, often the optimal objective value of the offline scenario, in which all information is known beforehand, is used as a bound. In our case, we use the path model with the actual forecasts to compute the optimal starting time slots of an instance in hindsight. Figure 5.12 shows the optimal distribution of starting time slots and the corresponding individual contributions given the knowledge of all PV uncertainty sets. The optimal offline objective of the instance is 20.891 kWh, showing an 'optimality gap' of less than 2.7% for the threshold used in Figure 5.11.

Figure 5.13 also shows that we cannot hope for a constant threshold, which leads to an optimal solution for all instances. Taking the smallest individual contribution of the optimal solution as the constant threshold would result in a solution similar to that of the low threshold presented in Figure 5.12. Generalizing this insight implies that there does not exist an optimal constant threshold policy for the online k-edge longest path problem.

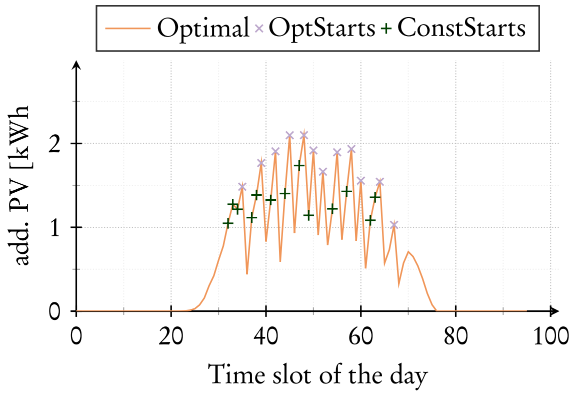


Figure 5.13: Contributions of an optimal solution. OptStarts denotes the optimal starting time slots of the rolling horizon, while ConstStarts denotes the time slots, in which the contribution is larger than the smallest optimal contribution.

Factor

Although it is not possible to derive an optimal online threshold policy to our problem, in practice it has been shown that simple online threshold algorithms often achieve good results (see e.g., [8, 268]). In the following, we, therefore, test the impact of the factor choice on the outcome of the online threshold algorithms.

Figure 5.14 displays the objective values of the online threshold algorithm for the whole range of percentiles and all factor choices introduced in Section 5.6.2 using $k = 12$ iterations per day. One key observation of Figure 5.14 is that the differences in performance between the various factors grow slightly with the percentile. As can be seen, the piece-wise constant factor performed best among all factors (which we also observed for the remaining error distributions and numbers of iterations not displayed in Figure 5.14). Therefore, we restrict our following analysis to the piece-wise constant factor.

Number of Iterations

Figures 5.15a - 5.15c show the results of the AR and HR approaches for the piece-wise constant factor for the whole range of percentiles and suitably chosen iterations for the three underlying error distributions. The displayed number of maximal iterations per day corresponds to various step sizes of the classical rolling horizon. Figure 5.16 displays the results for the PR and exponential based on [276] approaches for the same distributions and iterations. We compare the results to the (in hindsight) optimal path solution, denoted by OptPath.

We first analyze the impact of the maximal number of iterations on the solutions. Based on the results observed in Section 5.4, we expect to see an improvement

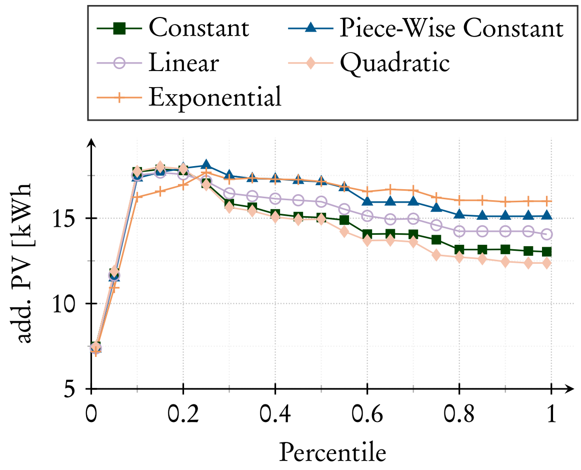


Figure 5.14: Contributions of uniform AR online threshold algorithms for various factors (marks) and percentiles (x-axis) for a time horizon of three days with $k = 12$ iterations per day.

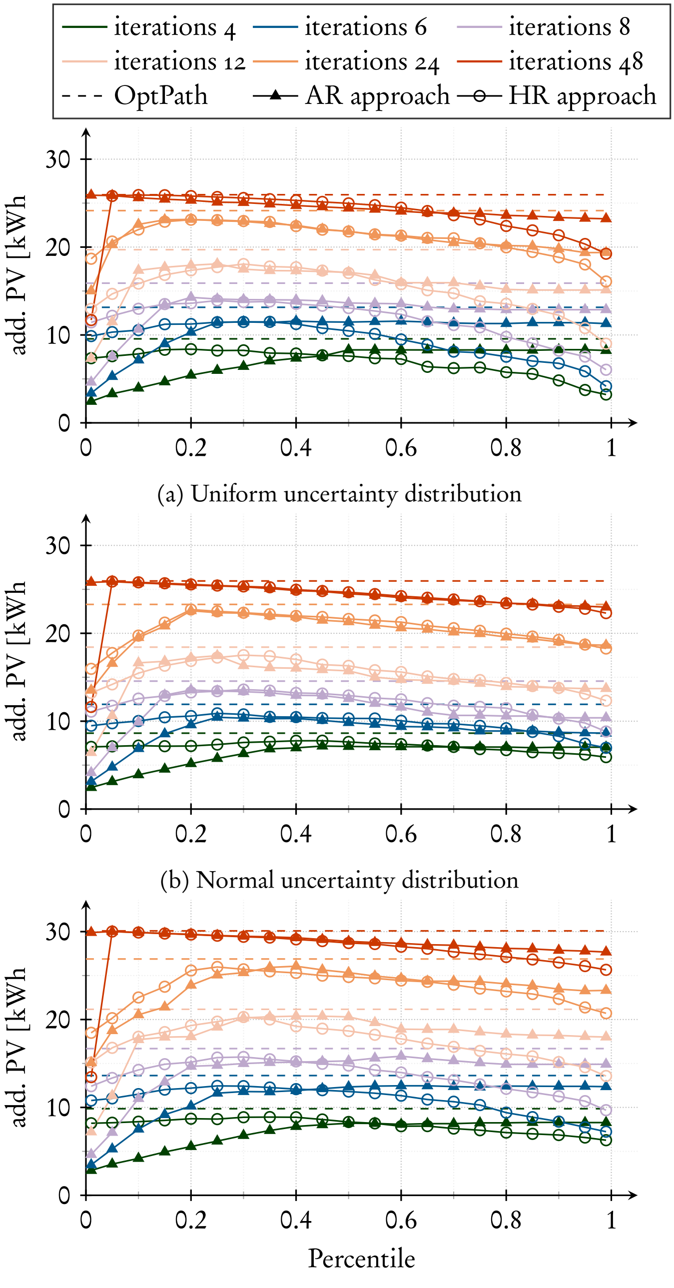
in objective value with an increasing number of iterations. Figures 5.15 and 5.16 confirm this expectation to a large extent. There are only a few small exceptions to this insight, in particular for extreme percentile choices. Nevertheless, in general, there is a clear distinction in the objective value between the different maximal numbers of iterations, also for the PR approach, see Figure 5.16. This improvement stems from the additional number of updated PV forecasts with (possibly) improved lower bounds on the PV generation and can be observed for all underlying probability distributions. In addition, it can be observed that the gap towards the optimal solution gets smaller the more iterations can be started.

Percentiles

Focusing on the percentile choice, we notice that for small and large values, the online threshold algorithms perform much worse, see Figures 5.15a - 5.15c. This can be explained by the resulting threshold values of the extreme percentile choices. As already mentioned, particularly large or small threshold values can decrease the performance of the overall online algorithm significantly. A balanced percentile choice between 0.15 and 0.5 on the other hand ensures a good performance, although small differences between the underlying probability distributions and approaches can be observed.

Approaches

Comparing the results of the AR, HR, and PR approaches with each other, some conclusions can be drawn. First of all, there does not seem to be a large

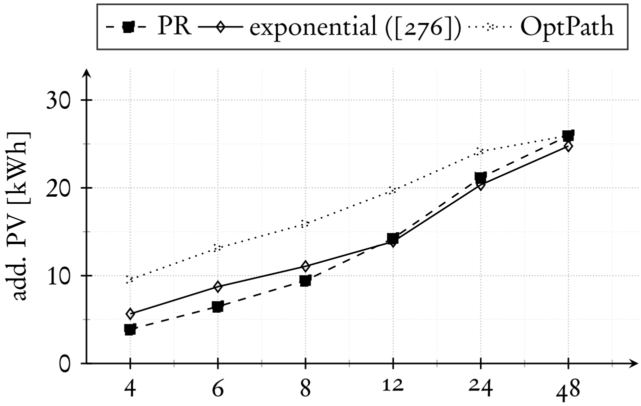


(a) Uniform uncertainty distribution

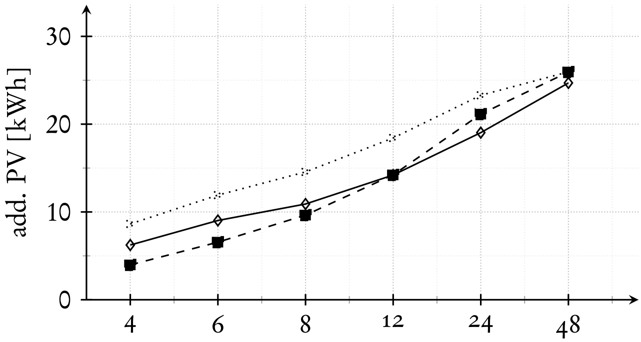
(b) Normal uncertainty distribution

(c) Shifted normal uncertainty distribution

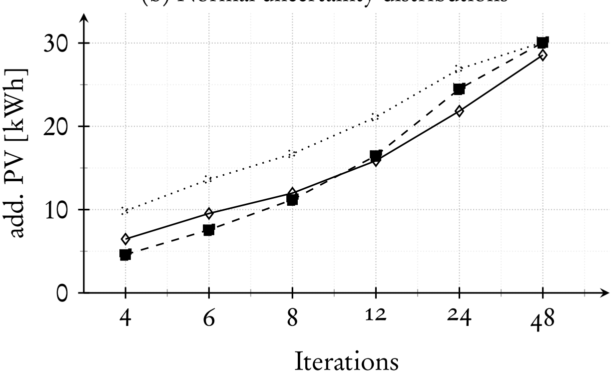
Figure 5.15: Contributions of online threshold algorithms for the AR and the HR approaches with the piece-wise constant factor and different numbers of iterations per day (colors) and percentiles (x-axis) for a time horizon of three days.



(a) Uniform uncertainty distribution



(b) Normal uncertainty distributions



(c) Shifted uncertainty distribution

Figure 5.16: Contributions of the PR model and the exponential ([276]) approach for various numbers of iterations (4 - 48).

difference between the AR and HR approaches w.r.t. their best objective value. In particular for the normal distribution (see Figure 5.15b), the two approaches seem to overlap to a high degree for a percentile larger than 0.2, with the best results usually achieved by a percentile choice between 0.2 and 0.3. For the uniform distribution, the results of the AR approach improve with increasing percentile for a few iterations, while for the HR approach, it seems to be the opposite. For a larger number of iterations, this observation does not hold any longer, although the AR approach seems to be less sensitive towards large percentile choices compared to the HR approach, which performs better for smaller percentile choices. The best percentile choice once again seems to be within the interval $[0.2, 0.3]$ in most cases. For the shifted normal distribution on the other hand the best percentile choice for the AR approach mostly changes to a slightly higher value between 0.4 and 0.6. The only exception is the largest number of iterations, for which a very small percentile choice performs best. Here, the increased percentiles balance out the rather neutral guess of average realizations compared to the distribution mean of 0.4. The HR approach on the other hand is not influenced by the mean of 0.4, as this information is already present in its historical data set.

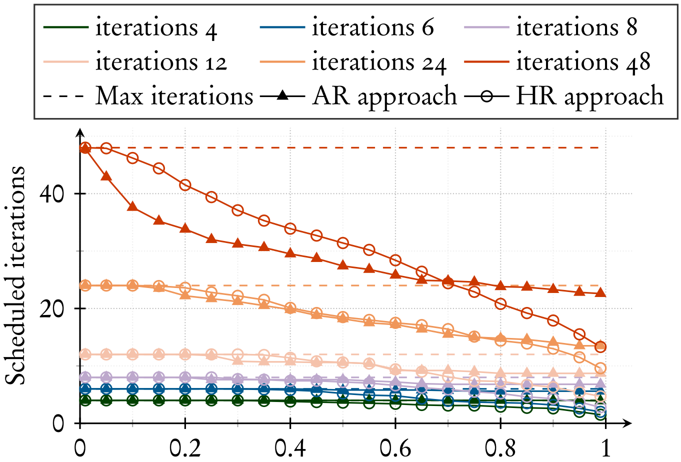
In contrast to the AR and HR approaches, the PR and the exponential approaches are independent of the percentile choice. Similarly to the other online approaches, they perform better for a very large number of iterations, while for fewer iterations the distance to the optimal solution grows considerably. A direct comparison to the AR and HR approaches reveals that the PR and the exponential approaches perform much worse.

Number of Scheduled Iterations

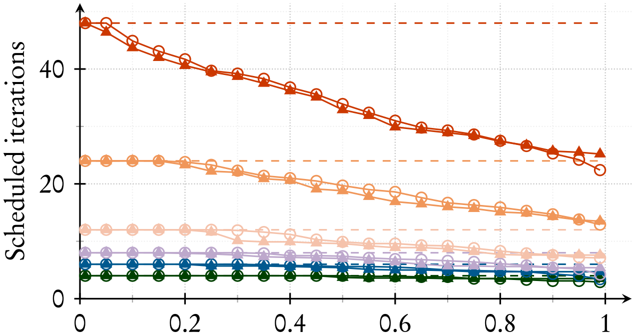
Within the previous analysis, we mainly focused on the objective value and ignored when and how many iterations were actually started. In contrast to the classical and the generalized rolling horizon schemes, we cannot guarantee how many iterations are started, as the online scheduling tool is quite sensitive towards the threshold, see also the analysis of Figure 5.12. However, based on the insights in Section 5.4, the number of iterations is still an important factor in achieving good results, and therefore, we now shortly focus on the number of iterations scheduled by the online threshold algorithm for various parameter choices.

Figure 5.17 displays the average number of scheduled iterations of the online rolling horizon scheme for one day and different uncertainty realizations. Based on the previous analysis, we only show the results for the AR and HR approaches for the piece-wise constant factor. We once again split up the analysis according to the different parameters:

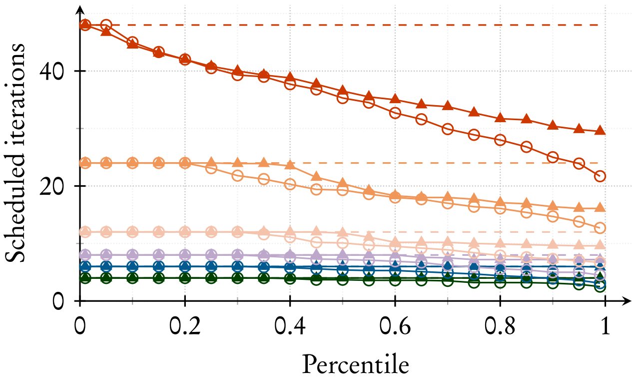
» *Percentiles*: At first glance, we directly notice that with increasing percentiles, fewer iterations are started. This observation is in line with the



(a) Uniform uncertainty distribution



(b) Normal uncertainty distribution



(c) Shifted uncertainty distribution

Figure 5.17: Average number of scheduled iterations of the online rolling horizon scheme for one day and various approaches and percentiles.

analysis of Figure 5.12, as a higher percentile results in a larger threshold, which in turn implies fewer iteration starts.

- *Iterations*: Analyzing the differences w.r.t. the allowed number of iterations, we notice that if only few iterations are allowed, then the (significant) decrease in scheduled iterations only starts with a percentile of around 0.6, while for a larger number of allowed iterations, the decrease already starts for a percentile between 0.05 to 0.4. This observation can be explained by the difference in (optimal) thresholds for various numbers of allowed iterations. If many iterations are allowed, then in the optimal solution, also time slots with a rather small individual contribution, such as in the early morning or late afternoon with only a small PV production, are chosen, see Figure 5.6. Compared to the large PV production in the middle of the day, there are large differences in the individual contributions, and therefore the threshold increases faster with increasing percentile. However, if only few iterations are allowed, then the optimal starting time slots usually are centered around midday, with similar individual contributions, and therefore the percentile change does not result in a large change in threshold.
- *Approaches*: Focusing on the differences between the approaches, that is the AR and the HR approach, we notice that they mostly start a similar number of iterations, however, the HR approach schedules fewer iterations for a large percentile compared to the AR approach. This can be explained by the way the threshold is computed. While the AR approach is based on the assumption of average realizations, the HR approach uses multiple data samples to compute optimal thresholds. Therefore, the probability of obtaining a few large thresholds out of the sample data is larger compared to the average realizations. Hence, for large percentiles, the threshold of the HR approach tends to also be larger than the threshold of the AR approach.
- *Uncertainty Probability Distribution*: Focusing on the differences w.r.t. the underlying probability distribution of the uncertainty realizations, we notice that the results are mostly similar to each other, with only minor differences. One interesting observation, which is in line with the analysis of Figure 5.15c, is that for the shifted normal distribution, the AR approach is able to schedule the maximally allowed number of iterations even for larger percentiles compared to the other two underlying probability distributions.

5.6.4 Comparison to the Generalized Rolling Horizon-Based Approach

In the previous analysis, we have shown that the online threshold algorithms work as hoped for. We analyzed the impact of the various parameters on the outcome of the algorithms and have shown that a clever combination of the parameters allows solutions, which are very close to optimality. However, the analysis only focused on the online scheduling algorithms on their own, without the energy management problem.

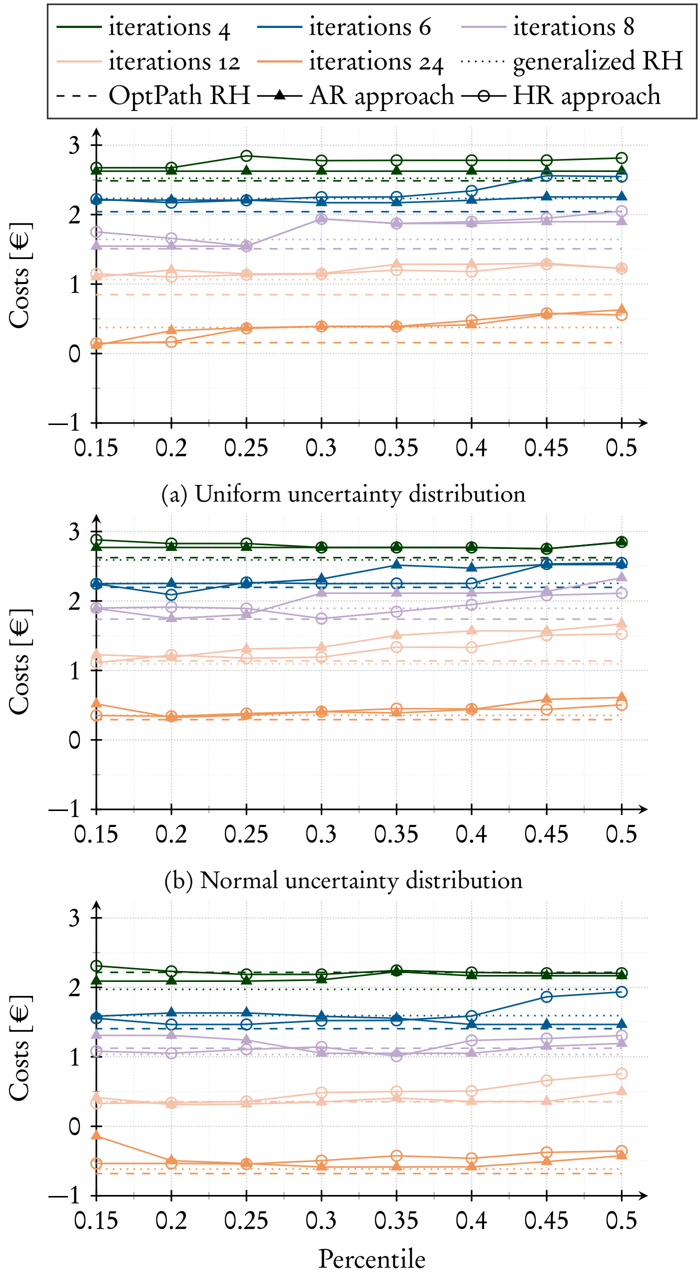
Within this section, we go beyond this individual analysis of the various aspects of the proposed online scheduling algorithms. We investigate whether the insights gained in the previous section transfer to the solutions when taking the whole online rolling horizon-based robust energy management approach into account. In addition to the objective value, which now represents the electricity costs of the microgrid, we also consider and discuss the impact of the online scheme on the local PV usage.

We compare the results of the online algorithms to the solutions of the starting time slots obtained by the optimal offline path solution, denoted by OptPath rolling horizon, as well as the classical and generalized rolling horizon versions, as presented in Sections Section 5.4 and 5.5. Due to the previous analysis, we mainly focus on the AR and HR approaches, as these obtained the best results for a wide range of iterations. We consider various step sizes of the classical rolling horizon and translate these into the corresponding maximal number of iterations for the dynamic and online rolling horizon models, e.g., a step size of 24 time slots results in 4 iterations per day. However, we do not consider the step size of 2 (respectively 48 iterations per day) anymore, as the results in the previous analysis already showed nearly optimal results. For the sake of clarity, we did not include the objective values of the classical rolling horizon approach in the figures but still refer to them within the analysis. Based on the results of Section 5.6.3, we restrict the analysis to the percentile range $[0.15, 0.5]$ as well as the piece-wise constant factor.

We start with the results based on uniformly random realizations. Figure 5.18 shows the objective function values, which represent the electricity costs of the microgrid, while Figure 5.19 shows the local PV usage of the solutions.

» At first glance, when directly comparing Figures 5.18a and 5.19, we already notice that the results regarding objective function and local PV usage rate seem to mirror each other to a high level of detail. This once again highlights the impact of the PV forecasts and generation on the objective value and strengthens our choice of using the PV forecasts as the underlying measure for the online algorithms within this application scenario.

» In general, the insights gained during the analysis of the online threshold algorithms also transfer to the results including the robust energy management scheme. The number of iterations has a significant impact on the solution, both regarding costs and local PV usage, and the more often an iteration can be started, the better the results. The individual percentile choices also align well with the previous results and in general, there is no clear difference between the AR and HR approaches, neither w.r.t.



(a) Uniform uncertainty distribution

(b) Normal uncertainty distribution

(c) Shifted normal uncertainty distribution

Figure 5.18: Objective value (in costs) of online rolling horizon scheme for various numbers of iterations (colors) and percentiles (x-axis) for a time horizon of three days.

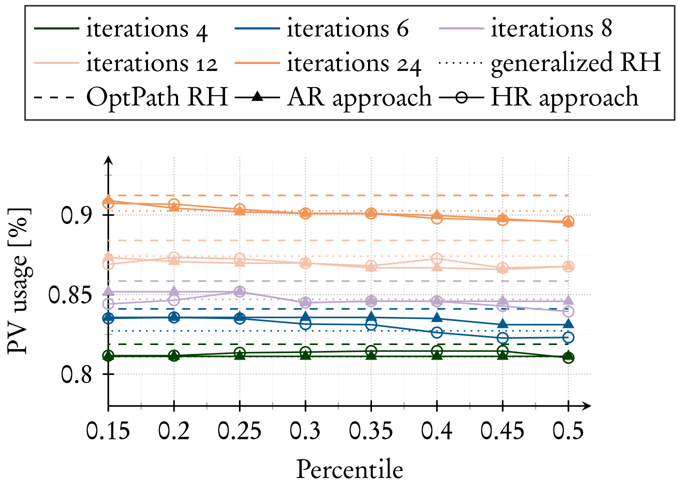


Figure 5.19: PV usage (in %) of online algorithms for various numbers of iterations (colors) and percentiles (x-axis) for a time horizon of three days with uniform uncertainty distribution.

the objective values nor regarding the PV usage. Both perform similarly when considering the percentiles and iterations.

» Compared to the generalized rolling horizon solution, the AR and the HR approach outperform it for suitably chosen percentiles both, in costs, as well as in local PV usage. The online algorithms achieve results that are up to 50% better compared to the generalized rolling horizon results, see Figure 5.18a. The results of the classical rolling horizon model are not displayed in the figures, as the objective value is much larger compared to all other approaches, with improvements of the online algorithms of over 85% compared to the classical rolling horizon. This also aligns well with the insights from Section 5.5, in which the generalized rolling horizon already clearly outperformed the classical version.

» Comparing the AR and HR approaches against the OptPath rolling horizon, which is based on the optimal offline starting time slots, as presented in the previous analysis, we notice that the more iterations can be started, the better the online algorithms perform. In a few cases, the objective values of the online approaches are even better than the ones of the optimal starting time slot rolling horizon model. At first glance, this may seem counterintuitive, as the OptPath model served as a bound on the optimal solution. However, the online threshold algorithms are solely based on the PV forecasts, while the underlying robust energy management problem also considers uncertainties in market prices, or EV and household load. Hence, different decisions taken during the robust energy management approach combined with uncertainty in market prices have led to a situation, in which the optimal starting time slots performed worse than the online starting time slots. When focusing on the PV usage (see Figure 5.19), which better represents the objective of the online threshold algorithms, the optimal starting time slot rolling horizon model clearly outperforms the online algorithms again.

The results for the normal (Figure 5.18b), respectively shifted normal distribution (Figure 5.18c) slightly differ from the uniform results. Nevertheless, the general insights from the analysis of the online scheduling algorithms, such as the impact of the number of iterations or the percentile choice on the objective value or the similarity of the AR and the HR approaches, are still valid. The main differences to the uniform uncertainty realizations are the results of the generalized rolling horizon framework, which are much better and often outperform the OptPath approach. Nevertheless, for selected iterations and percentiles, the online algorithms still achieve better results than the generalized or OptPath approach (see Figures 5.18b and 5.18c), although the improvements are much smaller compared to the uniform distribution case. The classical rolling horizon results are once again not displayed as these perform significantly worse than any of the other considered rolling horizon schemes, with improvements of the online algorithms of over 80%.

5.6.5 Discussion

Summarizing the previous analysis, we notice that the online algorithms clearly outperform the generalized rolling horizon model for the uniform distribution, while the results for the normal and shifted normal distribution are much more similar to each other. The OptPath approach, which served as an upper bound in the analysis of the online scheduling algorithms without the energy management approach, sometimes achieves worse results than the online or the generalized rolling horizon approaches. This can be explained by the additional uncertainty, such as e.g., uncertain market prices, which are not considered in the online threshold algorithm. The differences in performance between the underlying error distributions hint that the online algorithms are particularly useful in certain scenarios. Within the context of the energy management approach, the uniform error distribution could be seen as the representation of a particularly cloudy, but still sunny day, in which PV forecasts can change drastically within a very short time. Hence, both online algorithms are able to deal with such fluctuating forecasts much better than any offline algorithm, highlighting interesting application scenarios.

Another interesting insight from the analysis concerns the similarity between the AR and the HR approach. Even though the HR approach is based on much more detailed information in the form of multiple data sets following the same underlying unknown error distribution, the AR approach performed equally well, even if the mean of the underlying error distribution did not align with the zero mean assumption of the AR approach, as can be observed for the shifted normal distribution. Thus, we are able to design well-performing online algorithms using only very little additional information.

5.7 Conclusion

In this chapter, we presented various approaches to deal with uncertainty in data in the context of a joint energy management and trading problem for a microgrid. We first introduced concepts from robust optimization, before presenting the considered uncertainty within the energy management problem. We then proposed and tested two different techniques from robust optimization, each with its own advantages and shortcomings.

For the first approach, we focused on and used the concept of linear decision rules from adaptive robust optimization to deal with the uncertainty. The resulting solutions can be characterized by their ability to adapt to uncertainty realizations later on in time. This allows to adjust some of the decisions, such as the intraday market decisions or how much to charge or discharge the battery or the EVs, to the actual realizations of the PV generation or other uncertain parameters. This additional flexibility leads to improved objective values and average costs over a fully static robust solution at the cost of a larger mathematical model, which only needs to be solved once. Suitably chosen LDRs also allow to preserve the privacy of the realizations of some uncertain parameters, such as the household load or the EV demand. However, not all considered uncertain parameters could easily be included in the LDRs. In particular the uncertain EV arrival times did not fit well with the structure of the decision rules due to their rather binary nature. An implementation would have required a significant increase in variables and constraints, which may result in intractable models. An open research direction could investigate other ways to include uncertain parameters affecting whether constraints are created or not, such as e.g., the EV arrival time.

The second approach also uses a well-known technique from robust optimization, namely the combination of a static robust reformulation with a rolling horizon. This combination also allows to adapt some of the decisions later on in time, due to the re-optimization steps of the rolling horizon. In the analysis of the first implementation, we observed that solving several iterations of the rolling horizon led to reduced costs compared to solving the whole time horizon at once. In a deterministic setting, this could not happen, and in the following, we showed that the various sources of uncertainty within the energy planning problem differ in their impact on the objective value of the resulting solution. In particular, the time-dependent PV uncertainty contributed most to the improvement, and therefore we shifted the focus of the following analysis from the robust techniques to the impact of the starting time slots of the iterations as a means of improving the solution without additional iterations. Based on this insight, we first introduced the idea of a generalized rolling horizon scheme, which allows for a more flexible scheduling of the iterations, and then proposed a tailor-made scheduling tool, which identifies promising starting time slots for the iterations of the rolling horizon. The main idea of this scheduling tool is loosely based on the concept of the knapsack problem and we showed that a projection to the k-edge longest path problem exists, for which we present a polynomial-time dynamic programming approach. A comparison to the classical rolling horizon approach shows the potential of the generalized version and also highlights when the approach performs best. In the following, we identified a few weaknesses of the generalized rolling horizon scheme and addressed these with a further development. The resulting online rolling horizon framework allows to make the decision whether to start an iteration or not on the fly and can thereby react to unusually good or bad forecasts and observed realizations of the uncertainty. We proposed an online scheduling tool, which is based on the concept of the previous scheduling tool, and combined it with an online threshold-based algorithm. We then tested it against the generalized rolling horizon approach for various uncertainty realizations and could observe a clear improvement over the generalized rolling horizon approach for some realization scenarios, while for other scenarios, both approaches performed much more similarly. Based on these insights, a future research direction could be to combine both approaches with each other. This would allow for an algorithm, that is mostly predictable in when iterations are run. However, it would still be able to react to extreme forecasts and observations and thereby combines the best of both approaches with each other.

5.8 Appendix: Dynamic Programming Approach for k-edge longest path problem with fixed subset of nodes

The first dynamic programming approach identifies the h-edge longest paths between nodes $i_j, i_{j+1} \in \mathscr{M}$ for $h = 1, 2, \ldots, \min(k+1, i_{j+1} -_j)$. Let $L_h(i)$ denote the length of the longest path from node i_j to node $i_j < i \leq i_{j+1}$ with exactly h arcs. W.l.o.g., we assume that each node i has an arc (i, i) with length $c_{i,i} = 0$. Then the following recursive formulation

$$L_h(i) = \max_{i_j \leq l \leq i} (L_{h-1}(l) + c_{l,i}) \tag{5.23}$$

models the optimality of the longest path in a bottom-up approach. Define $L_1(i) = c_{i_j,i}$ to be the required first entries. Starting with longest paths of cardinality one to each following considered node, we iteratively extend the number of arcs within the paths. For each entry $L_h(i)$, we need to find the maximum value over a set of at most $|V|$ nodes. We need to do this for every node and at most k times, leading to a computation time of $\mathcal{O}(V^2 k)$ for each pair of nodes. Let $L_h(j)$ for $1 \leq h \leq \min(k+1, i_{j+1} - i_j)$ denote the longest paths with exactly h arcs from i_j to i_{j+1}.

The second dynamic programming approach is based on the results of the first one. That is, instead of using the original arc weights $c_{s,t}$, we use the longest paths $L_h(i_j)$. Let $L'_h(j)$ denote the length of the longest h-edge path from node 0 to node i_j. We once again use a recursive bottom-up formulation

$$L'_h(j) = \max_{1 \le g \le h} (L'_g(j-1) + L_{h-g}(j-1)). \tag{5.24}$$

Instead of extending the number of edges in the paths, as done in equation 5.23, we extend on the target node of the considered path. Hence, we start the dynamic programming approach with $L'_h(1) = L_h(0)$ for all h. The running time is then $\mathcal{O}(mk^2)$. Within each update $L'_h(i)$, we need to find the maximum of a set of cardinality at most k, and we need to repeat that at most mk times.

The total running time is then $\mathcal{O}(V^2k + mk^2)$.

It should be noted that the problem can also be solved via an LP, where one can show that the resulting matrix is totally unimodular using the theorem of Ghouila-Houri.

6

Grid constraints: Real-time balancing and control between microgrids

Abstract – *This chapter focuses on the large research field of power flow computations as a means to include grid constraints into local energy trading. The setting centers around a real-time control and balancing problem between microgrids, which aims to realize the planned day-ahead and intraday solutions of microgrids within the considered 15-minute time slots. To realize these solutions in real-time, a three-step framework is proposed. The first step ensures the feasibility of devices within the microgrids, while the second step focuses on the grid constraints of the connecting medium voltage grid using the DC power flow formulation due to the running time requirements of a real-time approach. In the last step, the solution is propagated into the individual microgrids, where the allocated power needs to be distributed among the devices and households. Within a case study, the proposed real-time control approach is analyzed in detail and found to be comparable to an optimal offline algorithm under some mild assumptions.*

6.1 Introduction

The third and last neglected aspect identified in Chapter 3 is the integration of the physical infrastructure into local energy trading. Most local energy trading approaches only focus on the flexibility offered by the various devices as well as the balancing of demand and supply, but ignore the impact of their proposed trades on the underlying electricity grid. Due to the ongoing electrification of residential heating and mobility and the increasing loads due to the PV generation, the energy transported within the electricity grid continues to increase, and

This chapter is based on [JH:5].

thereby also the burden on the electricity grid. Already today, large parts of the electricity grid in e.g., the Netherlands are reaching their capacity limits [190]. This development blocks the further electrification and installation of renewable energy sources (RES), which are required for the energy transition. Hence, to e.g., further install more RES in the electricity grid in the near future, some form of additional control regarding the capacity limits of the grid is needed.

Many of the day-ahead and intraday problems found in literature or proposed in Chapters 4 and 5 of this thesis operate on 15-minute time slots. These approaches view the problem of matching demand and supply from an energy perspective, thereby paying no attention to the power distribution within a single time slot. While this may be a reasonable assumption for the (long-term) day-ahead operation and corresponding markets, in the practical operation of the physical grid, demand, and generation are not equally distributed within each 15-minute time slot, and large fluctuations may appear. These fluctuations may lead to an excess of grid capacity limits, even if these limits were taken into account during the day-ahead or intraday operation phase. These fluctuations may lead to short-term overloads and congestion in the (distribution) grid, thereby significantly contributing to the aging of the physical infrastructure such as e.g., transformers and cables [50, 106, 124]. To avoid the resulting increased demand for maintenance, a more detailed view of the power profiles within these 15-minute time slots is required. Even though the flexibility and load of single households increase significantly with the addition of devices, such as a PV system, a battery, an EV, or a HP, its impact within the grid is still relatively small. However, many of the day-ahead and intraday approaches are based on a microgrid, which jointly manages its demand and supply. In such a case, the aggregated trades of a single microgrid may already be large enough to cause problems in the distribution grid.

Therefore, in this chapter, we focus on the real-time control and balance between microgrids. The considered setting consists of a set of connected, but independent microgrids and spans a single time slot of the day-ahead operation problem. We treat each microgrid as an active participant of the real-time control algorithm, which next to the implementation of the day-ahead plan also contributes to the feasibility of grid constraints of the connecting MV distribution grid. The relatively simple (radial) structure of the low-voltage (LV) grids connecting the households within a microgrid is left to the corresponding microgrids to handle. The households within the microgrids may be equipped with PV systems, batteries, and EVs, next to their household demand. See Chapter 2 for further details on the microgrid, as well as mathematical formulations of the devices.

In the last decade, many different approaches to real-time control have been proposed. In contrast to the mostly optimization-based EMS approaches for the day-ahead and intraday operation, real-time approaches are often based on (simple) rule-based control mechanisms to cope with the computational restrictions of real-time control. Furthermore, one of the main reasons for power quality issues in microgrids is a surplus of PV generation during times of low demand. There are two core research directions to tackle such issues. The first is to simply curtail the PV generation, while the second uses batteries to store some of the generation and thereby reduce the grid feed-in of electricity. Common approaches regarding the curtailment of (PV) generation are droop-control [121, 126, 198, 250] or the volt-watt scheme [71]. An important and challenging aspect of PV curtailment within microgrids is the fairness of the curtailment among different households (see e.g., [141, 259]). When using batteries to reduce the feed-in, it is not sufficient to focus only on the current situation and corresponding actions, as capacity and possible future problems and decisions already need to be considered. To still be able to compute solutions efficiently, Lyapunov optimization is often used as an online control approach for batteries to reduce peaks in demand or PV feed-in [1, 153, 221, 222]. Other approaches use model predictive control or reinforcement learning to incorporate additional aspects, such as ancillary services or voltage constraints into real-time control schemes [75, 188, 208]. Furthermore, in [247], a mixture between load curtailment and battery usage is proposed and in [91] a real-time P2P energy market is considered, which is solved using a novel online ADMM approach.

Another interesting way to deal with real-time control of batteries and loads without having to consider the uncertainty of future time slots is to combine (long-term) energy management approaches with real-time control. This idea has only recently seen more attention (see e.g., [34, 51, 52, 93, 94, 155, 173]). The main principle among these approaches is to use the day-ahead energy solution to guide the real-time control. To ensure feasibility, the day-ahead operation is often based on solution techniques, such as chance-constrained [51] or multi-stage stochastic optimization [93, 94] to account for the uncertainty in PV or demand forecasts. As already mentioned, the considered time slots usually encompass 15 to 60 minutes and the most common objective is to minimize the long-term costs of the considered system. The real-time component of the approaches then tries to realize the planned solution within a single (day-ahead) time slot. Using the targets, provided by the day-ahead solution, even very simple control approaches can achieve good results. These real-time approaches can range from simple rules [51, 93, 94, 173] or look-up-tables [34] to more sophisticated mathematical optimization models [52, 155]. The objective of the real-time component usually focuses on minimizing the deviations from the planned day-ahead schedule. Another common aspect of the considered literature is that they focus on a few devices, such as a PV system, a battery, and possibly an additional (household) load. Only in [155] and in [173] multiple (distributed) devices are modeled and controlled within the setting of a microgrid. Due to the focus on day-ahead EMSs and real-time control of only a single household or small energy system, the constraints of the underlying grid, which are usually an important aspect of real-time control, are mainly ignored. Only [155] considers power flow computations in both, day-ahead and real-time. Summarizing, there is a gap in the current literature on the combination of distributed EMSs and real-time control or balancing between microgrids, whereby also grid limitations are taken into account.

To close this gap, we present a real-time control algorithm, that implements the day-ahead solution as closely as possible. Thereto, the proposed approach uses the planned day-ahead solutions of the microgrid to guide its online decisions. The main objective of the approach can be split up into two aspects: The first objective is to minimize the deviations in the real-time power exchange with the market from the planned power exchange level. The second objective is to ensure that each device reaches its planned state (of charge) at the end of the time slot. To achieve these objectives, each microgrid may use the flexibility of its local devices, such as batteries or PV systems, and may also trade real-time surplus of electricity with neighboring microgrids. The proposed algorithm can be described as a modular three-step framework, which can easily be adapted to other real-time scenarios and settings.

The chapter is structured as follows: In Section 6.2, the considered setting and main motivation are presented in detail. In Section 6.3, the mathematical formulation of flexibility for various devices is first introduced, before presenting an aggregated microgrid and system model. In Section 6.4, the three-step framework, including the different components is proposed together with possible extensions and alternatives for the individual parts. In Section 6.5, the proposed real-time control approach is tested and analyzed. The work is concluded with a short summary and discussion in Section 6.6.

6.2 Setting

In the following, we introduce the considered setting of both, the day-ahead as well as the real-time layer. Hereby, the main focus lies on the real-time setting.

6.2.1 Day-Ahead Energy Operation

We consider a day-ahead energy management or trading problem where the energy usage of various households and their devices within a microgrid is coordinated and planned for the next day. The corresponding approach has to ensure that the demand for each household is satisfied for that day. Hereby, device constraints, such as e.g., charging and discharging limits or capacity constraints of batteries or EVs, have to be respected. In most cases, the main objective of a corresponding EMS is to maximize the financial profit (or minimize costs) for the whole microgrid. In some cases, other or additional objectives, such as e.g., minimizing the corresponding greenhouse gas emissions or minimizing the comfort loss of households, are also considered. As the name already indicates, the day-ahead EMS runs one day before the actual realization, and the considered time horizon usually spans the whole day, although there are also cases, in which a larger time horizon is considered. For the operation, the time horizon is split up into non-overlapping time slots (in general of length 15 to 60 minutes). For each such time slot, an energy schedule has to specify how much energy each device either consumes or produces during that time slot. In addition, for each time slot, the amount of produced and bought energy has to be equal to the amount of consumed and sold energy. Hence, a solution of the day-ahead EMS consists of a set of energy profiles, which defines the planned energy usage of each device for each time slot, while always maintaining the balance between demand and supply.

However, due to the time distance between decision-making and realization, deviations from the planned (household) demand or (PV) production occur. In addition, some (necessary) simplifications are included in the model due to the discrete time slot structure. These simplifications may cause problems in the real-time implementation of the day-ahead solution. If for instance, the forecast for the PV generation and the household demand for a certain time slot are equal, then from the day-ahead perspective, the solution to use the PV generation to satisfy the household demand is a feasible solution. When zooming into this specific time slot, however, in general, neither the household demand nor the PV generation is equally spread among the 15 minutes, and (large) differences and mismatches in their power profiles may appear. These differences may pose serious problems to the electricity system, as the system based on the day-ahead solution assumes that it has no energy exchange with the household. Taking such short-term fluctuations already in the day-ahead stage into account requires a finer time granularity, which results in two major problems. The first one concerns the complexity and size of the resulting optimization model, which may not be computationally tractable any longer. The second problem concerns the required data. It is well known that demand and production for larger time windows are much easier to predict and that the resulting values are more accurate, as short-term fluctuations within the time window may cancel out each other. On the other hand, the required time granularity has to be short enough to capture the occurring fluctuations in household demand and PV generation. However, it is hard or even impossible to predict these values accurately over a longer time horizon. Based on this, it is not feasible to alter the day-ahead EMS approach to also be able to capture the short-term fluctuations of demand and production. Therefore, we propose to add a real-time control approach, which deals with the short-term power differences in production and consumption in an online way.

6.2.2 Real-Time Power Control

In the real-time domain, the microgrid has to realize its planned day-ahead schedule taking into account the realizations of PV generation and the household base load. Hereby, the focus is on a single day-ahead time slot of e.g., 15 minutes. For the real-time control, this interval is split up into even smaller time slots, denoted by time slices of length Δt. We denote the set of time slices by $\Delta\mathcal{T}$. For each of these time slices, demand needs to be equal to supply, whereby the actual realizations of PV and household load are revealed only at the beginning of their corresponding time slice. Therefore, the real-time control algorithm has to work in an online fashion, only considering (and knowing information about) the current time slice, as well as past decisions. The made decisions for the current time slice are then realized and the algorithm proceeds with the next time slice. As the goal is to realize the day-ahead solution as closely as possible, we use the planned schedule to guide the online real-time control algorithm in the right direction. In the following, we first introduce the required information from the day-ahead solution:

» *Planned market decisions*: $\tilde{x}^M$ denotes the planned aggregated amount of energy bought or sold at the day-ahead and intraday markets for the considered time slot.

» *Planned Battery decisions*: $\tilde{E}^{B,k}$ denotes the planned energy within battery k at the end of the time slot, and $E_0^{B,k}$ denotes the initial energy within battery k at the start of the considered time slot.

» *Planned EV decisions*: $\tilde{E}^{EV,h}$ denotes the planned energy within EV h at the end of the time slot, and $E_0^{EV,h}$ denotes the initial energy within EV h at the start of the considered time slot.

» *Actual household demand*: P^{HL} denotes the (aggregated) household load power profile of a microgrid during the considered time slot, and P_t^{HL} denotes the expected load of time slice t, which is only revealed just before time slice t.

» *Actual PV generation*: P^{PV} denotes the (aggregated) PV generation power profile of a microgrid during the considered time slot, and P_t^{PV} denotes the realized PV generation of time slice t, which is only revealed just before its corresponding time slice t.

In this work, we aim to precisely follow the planned schedule of the batteries and EVs on the time slot level. Hence, the microgrid has to ensure that the actual energy within the batteries and EVs at the end of the time slot is equal to the planned amount $\tilde{E}^{B,k}$, respectively $\tilde{E}^{EV,h}$. However, as the aggregated realized PV generation, as well as household load, may differ from the predicted amount based on which the day-ahead solution was calculated, we do not require that the actual energy exchange of the microgrid with the markets is equal to the planned energy exchange. Nevertheless, we try to minimize the sum of squared differences between the realized power exchange profile with the market and the planned power exchange level. Given the constant planned power exchange level, this results in a power exchange profile as flat as possible, which thereby also minimizes short-term fluctuations in power delivery or feed-in.

To achieve the specified objectives, the microgrid can use the flexibility of its devices, in particular of the batteries and EVs, as well as the option of PV curtailment. If this flexibility is not sufficient to keep the profile of the market exchange constant throughout the whole time slot, there are two options. The first one is to trade power with neighboring microgrids, which may have flexibility left. Thereby, the goal is to keep the power exchange with the market at the planned level. If the flexibility of other microgrids is still not sufficient, the power exchange with the markets may be increased (or decreased) to ensure a balance between demand and supply at the cost of fluctuations in the power exchange with the markets.

Both, the trading with other microgrids as well as the adaption of the exchange with the market, impacts the underlying electricity grid. Therefore, we have to ensure that the grid limitations are respected by the updated electricity trading. We do so by means of power flow computations, which are based on information on the underlying electricity grid. For the sake of simplicity, we assume that the connecting MV grid has a single connection to the main grid, and thereby to the electricity markets.

6.3 Mathematical Modeling

Based on the above-introduced setting and goal of the real-time control approach, we first focus on the modeling of a single microgrid. We present an approach to project the flexibility of devices for the whole 15-minute time slot onto the current time slice t while ensuring feasibility w.r.t. the day-ahead targets of the devices. We then proceed with an aggregation of all flexibility within a microgrid and present the microgrid model for a single time slice. The second focus of this section is on a model on the system level, which merges multiple microgrids. For this, we combine the individual microgrid models and add constraints modeling the P2P trading as well as the power flow constraints.

6.3.1 Microgrid Model

In the following, we focus on the mathematical modeling of devices and the objective of a microgrid i for a single time slice t. Due to the very short time length of a time slice, denoted by Δt (e.g., 1-60 seconds), we model the variables, constraints, and the objective using power as the main unit. We thereby deviate from the energy modeling perspective of the day-ahead and intraday operation problem as presented in Chapter 2. However, we keep the notation the same.

Device Flexibility

In this section, we present a way to model the use of flexibility of devices for a single time slice, while ensuring feasibility of the day-ahead solution. We use the battery flexibility as the main example for devices, that connect multiple time slices with each other. Furthermore, we shortly specify how the flexibility can be modeled for the remaining considered devices.

Based on the standard multi-time slice formulation of a battery as introduced in Section 2.3, we derive upper and lower bounds on the device flexibility for a single time slice. For the sake of simplicity, we omit the indices denoting microgrid i and battery k. The standard multi-time slice constraints for the operation of a battery are

$$0 \leq E_0^B + \eta \sum_{s=1}^{t} x_s^{B,C} \Delta t - \frac{1}{\eta} \sum_{s=1}^{t} x_s^{B,D} \Delta t \leq C^B \quad \forall t \in \Delta\mathcal{T}, \tag{6.1}$$

$$0 \leq \eta x_t^{B,C} \leq L^{B,C} \quad \forall t \in \Delta\mathcal{T}, \tag{6.2}$$

$$0 \leq \frac{1}{\eta} x_t^{B,D} \leq L^{B,D} \quad \forall t \in \Delta\mathcal{T}, \tag{6.3}$$

$$E_0^B + \eta \sum_{s=1}^{T} x_s^{B,C} \Delta t - \frac{1}{\eta} \sum_{s=1}^{T} x_s^{B,D} \Delta t = \tilde{E}^B, \tag{6.4}$$

where $x_t^{B,C}$ ($x_t^{B,D}$) corresponds to the external charging (discharging) power during time slice t. Constraint (6.1) ensures that for all time slices, the energy within the battery is between 0 and its capacity C^B. Constraints (6.2) and (6.3) impose given (internal) bounds on the charging and discharging power, while constraint (6.4) ensures that the energy within the battery at the end of the time slot is equal to the planned energy $\tilde{E}^B$. Note that in contrast to the battery model in Section 2.3, we use internal bounds on the charging and discharging power to make the following reformulations easier.

To reformulate these constraints into a single-time slice model for time slice t, we first reformulate constraints (6.1) and (6.4). Let E_t^B denote the energy within the battery just before time slice t. Constraint (6.1) for time slice t then simplifies to

$$0 \leq E_t^B + \eta x_t^{B,C} \Delta t - \frac{1}{\eta} x_t^{B,D} \Delta t \leq C^B. \tag{6.5}$$

Constraints (6.2) and (6.3) already consider only variables for time slice t. The only remaining issue for the single-time slice model is to guarantee that the planned energy $\tilde{E}^B$ is achieved at the end of the time slot. One simple approach is to backlog how much energy has to be within the battery at the end of time slice t to still be able to achieve the required energy $\tilde{E}^B$ by the end of the time slot. Hence, for the charging and discharging decision of time slice t, we have the following restriction on the energy within the battery at the end of the time slice:

$$\tilde{E}^B - (T-t) L^{B,C} \Delta t \leq E_t^B + \eta x_t^{B,C} \Delta t - \frac{1}{\eta} x_t^{B,D} \Delta t \leq \tilde{E}^B + (T-t) L^{B,D} \Delta t. \tag{6.6}$$

We can now differentiate between charging and discharging and thereby receive the following bounds:

$$\frac{1}{\eta}\left(\frac{\tilde{E}^B - E_t^B}{\Delta t} - (T-t) L^{B,C}\right) \leq x_t^{B,C} \leq \frac{1}{\eta}\left(\frac{\tilde{E}^B - E_t^B}{\Delta t} + (T-t) L^{B,D}\right), \tag{6.7}$$

$$-\eta(\frac{\tilde{E}^B - E_t^B}{\Delta t} + (T-t)L^{B,D}) \leq x_t^{B,D} \leq -\eta(\frac{\tilde{E}^B - E_t^B}{\Delta t} - (T-t)L^{B,C}). \quad (6.8)$$

In case the lower bound of either constraint (6.7) or (6.8) is strictly positive, we are forced to charge, respectively discharge to still be able to achieve the planned energy at the end of the time slot. In case both lower bounds are negative, together with constraints (6.2), (6.3) and (6.5) we simply can use a single battery variable x_t^B with the following bounds:

$$l_t^B = \eta \max\{\frac{-E_t^B}{\Delta t}, -L^{B,D}, (\frac{\tilde{E}^B - E_t^B}{\Delta t} - (T-t)L^{B,C})\}, \quad (6.9)$$

$$u_t^B = \frac{1}{\eta} \min\{\frac{C^B - E_t^B}{\Delta t}, L^{B,C}, (\frac{\tilde{E}^B - E_t^B}{\Delta t} + (T-t)L^{B,D})\}. \quad (6.10)$$

The EV flexibility can be treated the same way as the battery flexibility since the considered time horizon is just a single day-ahead time slot for the real-time approach, and therefore, each EV is considered to be either available and can be charged and discharged, or is not available, which renders the flexibility to 0.

The PV generation and the load-supply balance constraints can be modeled in a straightforward manner, as these only contain variables of the current time slice t, leading to the following device flexibility constraint for time slice t:

$$0 \leq x_t^{PV} \leq P_t^{PV}, \quad (6.11)$$

for the PV generation, and

$$x_t^M + x_t^{PV} - \sum_{k \in \mathcal{N}_B} x_{k,t}^B - \sum_{h \in \mathcal{N}_{EV}} x_{h,t}^{EV} = P_t^{HL}, \quad (6.12)$$

for the supply-demand-balance constraint of the microgrid for time slice t. Hereby, N_B (N_{EV}) represents the set of batteries (EVs) within the considered microgrid.

Aggregation of Flexibility

The flexibility model of a microgrid for time slice t can be further simplified by combining the flexibility of all devices within the microgrid into a single variable x_t^D:

$$x_t^D = P_t^{HL} - x_t^{PV} + \sum_{k \in \mathcal{N}_B} x_t^{B,k} + \sum_{h \in \mathcal{N}_{EV}} x_t^{EV,h}. \quad (6.13)$$

The corresponding upper and lower bounds of the resulting single device variable are then

$$u_t^D = P_t^{HL} + \sum_{k \in \mathcal{N}_B} u_t^{B,k} + \sum_{h \in \mathcal{N}_{EV}} u_t^{EV,h}, \quad (6.14)$$

and

$$l_t^D = P_t^{HL} - P_t^{PV} + \sum_{k \in \mathcal{N}_B} l_t^{B,k} + \sum_{h \in \mathcal{N}_{EV}} l_t^{EV,h}, \tag{6.15}$$

where $u_t^{B,k}$ and $u_t^{EV,h}$, respectively $l_t^{B,k}$ and $l_t^{EV,h}$, correspond to the upper (lower) limits of the device flexibility of battery k and EV h as derived in (6.9) and (6.10). Note, that the (aggregated) household load of a microgrid, P_t^{HL}, can be seen as a variable with lower and upper bounds of P_t^{HL}. This aggregation of individual device flexibility leads to the following constraint

$$l_t^D \leq x_t^D \leq u_t^D. \tag{6.16}$$

The above aggregation is also an advantage regarding the privacy of data and information of individual devices and households within the microgrid. Due to the aggregation, no detailed, individual device information can be accessed by involved parties outside the microgrid.

Single-Time Slice Microgrid Model

As explained in Section 6.2, the objective of the microgrid is to achieve a flat power exchange profile with the market. Hence we introduce the market exchange variable $x_{i,t}^M$ for microgrid i and time slice t. Due to the focus on a single time slice at each iteration, we introduce a parameter X_i for each microgrid, which represents the desired power exchange level with the markets. To achieve a flat profile, we initially set the value to the average power required throughout the whole time slot to satisfy the planned energy exchange with the market. To reach this value X_i, microgrid i may use its internal (device) flexibility, as derived in Section 6.3.1. However, the flexibility may not be sufficient to achieve the desired exchange level. In such a case, microgrid i may also directly trade with neighboring microgrids j and thereby use the P2P trading component. Let $\mathcal{MG}$ denote the set of all microgrids, and let $x_{i,j,t}^{P2P}$ denote the power traded from microgrid i to microgrid j $(i, j \in \mathcal{MG})$, whereby positive values represent an import of power from j to i and negative values an export. Combining all three aspects, we have the following single-time slice microgrid model for microgrid i and time slice t:

$$\min (x_{i,t}^M - X_i)^2 \tag{6.17}$$

$$\text{s.t. } l_{i,t}^D \leq x_{i,t}^D \leq u_{i,t}^D, \tag{6.18}$$

$$x_{i,t}^M + \sum_{j \in \mathcal{MG}} x_{i,j,t}^{P2P} = x_{i,t}^D. \tag{6.19}$$

6.3.2 System Model

Within the overall system model, we consider a set of individual microgrids that are connected by an electricity grid structure. To model this overall system, we need to add further constraints to align the P2P decisions between microgrids and to model the power flow computations for the grid connecting the microgrids.

Peer-to-Peer Trading

Within the single microgrid model, the P2P trading variables $x_{i,j,t}^{P2P}$ have already been introduced and used within the demand-supply balance constraint. However, in the system model, connecting the models of various microgrids with each other, we need to ensure that the power microgrid i sends to microgrid j is consistent with what microgrid j receives from microgrid i. Therefore, we introduce the following constraint

$$x_{i,j,t}^{P2P} + x_{j,i,t}^{P2P} = 0 \quad \forall i, j \in \mathscr{MG}. \tag{6.20}$$

Power Flow

Let the underlying MV grid connecting the given microgrids consist of a set of buses, denoted by $\mathscr{N}$, and a set of lines $\mathscr{L} \subset \mathscr{N} \times \mathscr{N}$, connecting the buses. We assume, that each microgrid can be linked to a bus in the electricity grid, implying that $\mathscr{MG} \subseteq \mathscr{N}$. Let $L_{i,j}^{\max}$ denote the thermal limit of the line $(i, j) \in \mathscr{L}$ and let $x_{i,j}$ denote its reactance. Both, $L_{i,j}^{\max}$ and $x_{i,j}$ are parameters, specifying characteristics of the lines of the electricity grid and are assumed to be known.

Based on decades of research on power flow computations, various power flow formulations have been developed and analyzed in detail (see e.g., [172], [280]). Due to the strict time requirements of a real-time control approach, as well as the possibility to derive an analytical solution approach, we focus on the DC power flow formulation. In addition, this formulation can be applied to a wide range of grid topologies, which fits well with the considered MV grid, which can range from radial to ring or meshed structures. The DC power flow formulation is an approximation of the AC power flow equations [14] and is derived based on three main assumptions and simplifications:

1. The resistance of the lines is negligible.
2. The bus voltage magnitudes are approximately 1.
3. The voltage angle difference $\delta_{i,j}$ for lines (i, j) are small and thereby $\cos(\delta_{i,j}) \approx 1$ and $\sin(\delta_{i,j}) \approx \delta_{i,j}$.

These assumptions simplify the original (AC) power flow equations significantly by removing some variables and constraints, leading to a set of linear constraints, which can be solved efficiently. However, it should be noted that due to the simplification, only the thermal capacities of the network are considered and voltage constraints are ignored.

Within this system model, we have to ensure that the power flows within the network, resulting from the trading decisions of the microgrids, respect the given network constraints. For this, the resulting power flows within the grid have to be determined.

$p^L_{i,j}$ denotes the real power flow in the line $(i,j)\in\mathcal{L}$ and let θ_i be the voltage angle at bus i. These are the two variables in the model and they are strongly connected to the power generation and consumption in the buses of the grid. The basic DC power flow equations are:

$$p^L_{i,j} = \frac{1}{x_{i,j}}(\theta_i - \theta_j) \quad \forall (i,j)\in\mathcal{L}. \tag{6.21}$$

Next to these power flow laws, flow balance constraints link the power flow over lines to the generation and consumption at the buses:

$$x^D_i = \sum_{(i,j)\in\mathcal{L}} p^L_{i,j} \quad \forall i\in\mathcal{N}. \tag{6.22}$$

W.l.o.g., we define $x^D_i = 0$ for all buses, which are neither a microgrid nor the market (i.e. for all $i\in\mathcal{N}\setminus\mathcal{MG}$). To limit the power flow over a line (i,j) to its thermal limits, we add the following constraint:

$$-L^{\max}_{i,j} \le p^L_{i,j} \le L^{\max}_{i,j} \quad \forall (i,j)\in\mathcal{L}. \tag{6.23}$$

Single-Time Slice System Model

Based on the presented microgrid model as well as the power flow constraints and the P2P constraints, the overall system model for a single time slice t is given by:

$$\min \sum_{i\in\mathcal{MG}} (x^M_{i,t} - X_i)^2 \tag{6.24}$$

$$\text{s.t. } l^D_{i,t} \le x^D_{i,t} \le u^D_{i,t} \quad \forall i\in\mathcal{MG}, \tag{6.25}$$

$$x^M_{i,t} + \sum_{j\in\mathcal{MG}} x^{P2P}_{i,j,t} = x^D_{i,t} \quad \forall i\in\mathcal{MG}, \tag{6.26}$$

$$x^{P2P}_{i,j,t} + x^{P2P}_{j,i,t} = 0 \quad \forall i,j\in\mathcal{MG}, \tag{6.27}$$

$$p^L_{i,j,t} = \frac{1}{x_{i,j}}(\theta_i - \theta_j) \quad \forall (i,j)\in\mathcal{L}, \tag{6.28}$$

$$x^D_{i,t} = \sum_{(i,j)\in\mathcal{L}} p^L_{i,j,t} \quad \forall i\in\mathcal{N}, \tag{6.29}$$

$$-L^{\max}_{i,j} \le p^L_{i,j,t} \le L^{\max}_{i,j} \quad \forall (i,j)\in\mathcal{L}. \tag{6.30}$$

In the next section, we present an efficient algorithm to solve this optimization problem.

6.4 Real-Time Control Algorithm

In the following, we first give a high-level view of the algorithm, before explaining the individual steps in detail. After the explanation, we provide an outlook on possible extensions or alternatives to solve this problem.

6.4.1 Three-Step Framework

The high-level idea of the real-time control algorithm can be split up into three main steps:

1. The first main step is to create a device-feasible solution. We first assign to each microgrid its 'ideal' power exchange with the market, hereby not taking into account whether this solution is feasible w.r.t. the device flexibility or not. Afterward, each microgrid communicates either its upward and downward flexibility or its surplus or demand in case the ideal power exchange cannot be realized with its flexibility. If at least one microgrid is device infeasible, the P2P trading option between microgrids and the option to increase or decrease the power exchange with the market is enabled. To determine corresponding trades between microgrids, a min-cost flow problem is formulated, which can be solved efficiently.
2. Based on the resulting device-feasible solution, the second step is to ensure that the solution is also grid feasible. Using power flow equations, we compute the power flow on the lines of the electricity grid. If any thermal line limit is exceeded, a repair algorithm enables additional trades between microgrids and the market to achieve a grid-feasible solution, which maintains the feasibility w.r.t. the device flexibility. The repair algorithm is based on power transmission distribution factors (PTDF), which are a reformulation of the classical DC power flow equations (6.21) and (6.22). The problem is then formulated as a simple linear program with a quadratic objective, which can also be solved efficiently.
3. The resulting solution is both, grid and device feasible, and is then communicated to each microgrid in the third step. Each microgrid can then choose its own way to allocate its corresponding power among the available devices.

Algorithm 3 depicts the real-time control algorithm over a given time slot, split into a set $\Delta\mathcal{T}$ of time slices. The control algorithm is based on the three-step framework, which is deployed for every time slice $t \in \Delta\mathcal{T}$.

In the following, we explain each step in detail.

6.4.2 Device Feasibility

The main goal of the first step is to create a solution for the current time slice t, which does not violate any device constraints. The secondary objective is to keep

Algorithm 3: Three-Step Real-Time Control

for $t \in \Delta\mathcal{T}$ **do**
  1. create initial solution $x^M_{i,t} = X_i$ for each microgrid i;
  if $x^M_{i,t} \notin [l^D_{i,t}, u^D_{i,t}]$ for some $i \in \mathcal{MG}$ **then**
    Enable P2P trading with other microgrids and the markets by solving **Min-Cost Flow Problem**;
  2. Calculate power flow;
  if Line limits are exceeded **then**
    Repair solution by solving **Repair Problem**;
  3. Update parameters;

the power exchange with the market as close as possible to the given value X_i for each microgrid. Therefore, the algorithm creates a first solution by assigning each microgrid its ideal power exchange X_i. If this power exchange is feasible for each microgrid, the algorithm continues with the second step, namely checking the grid constraints. However, if for some microgrid i, $x^M_{i,t} = X_i \notin [l^D_{i,t}, u^D_{i,t}]$, then we enable the P2P trading between microgrids and the market to reach a device feasible solution.

Min-Cost Flow Problem

Given the initial solution for each microgrid, we solve a min-cost flow problem to reach device feasibility. The resulting flow can then be translated into P2P trades between microgrids (and the market). We first split up the set of microgrids into three sets, which form the basis of the graph, on which the min-cost flow problem is solved.

Let $\mathcal{D} = \{i \in \mathcal{MG} : X_i \leq l^D_{i,t}\}$ be the set of microgrids, for which the ideal power is not sufficient to satisfy their minimal demand, let $\mathcal{S} = \{i \in \mathcal{MG} : X_i \geq u^D_{i,t}\}$ be the set of microgrids, where the maximal device flexibility is not sufficient to consume the ideal power, and let $\mathcal{F} = \mathcal{MG} \setminus \{\mathcal{D} \cup \mathcal{S}\}$ denote the set of remaining microgrids, which are device feasible. Additionally, define $x(\mathcal{D}) = \sum_{i\in\mathcal{D}} l^D_i - X_i$ to be the total demand, which still needs to be provided and $x(\mathcal{S}) = \sum_{i\in\mathcal{S}} X_i - u^D_i$ to be the total surplus from microgrids in $\mathcal{S}$.

The main idea is to use the microgrids in $\mathcal{S}$ as sources of flow, the microgrid in $\mathcal{D}$ as sinks, and microgrids in $\mathcal{F}$ and the market as both, sources or sinks, depending on the current needs. There are three different situations regarding the total demand or surplus of the whole set of microgrids. If $x(\mathcal{S}) - x(\mathcal{D}) > 0$, we have a surplus of power and need to distribute the remaining part among the microgrids in $\mathcal{F}$ or the market, which then act as sinks. If $x(\mathcal{S}) - x(\mathcal{D}) < 0$, then the microgrids in $\mathcal{S} \cup \mathcal{D}$ are not able to satisfy their total consumption and

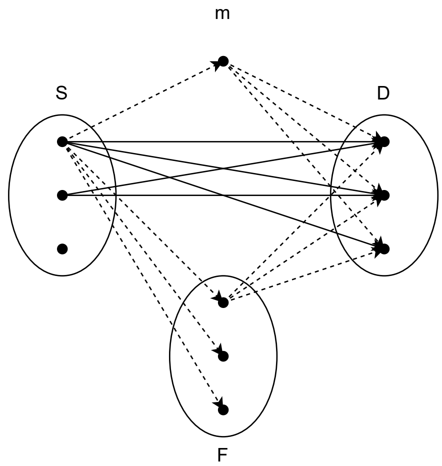


Figure 6.1: Sketch of the graph consisting of the microgrid sets $\mathscr{S}$, $\mathscr{D}$, $\mathscr{F}$ and m. The solid arcs represent connections which are always part of the graph, while the dotted ones depend on the case.

we need to distribute power from microgrids in $\mathscr{F}$ to microgrids in $\mathscr{D}$ or buy additional power from the market. If $x(\mathscr{S}) - x(\mathscr{D}) = 0$, we can restrict the P2P trading scheme to microgrids in $\mathscr{D}$ and $\mathscr{S}$.

Depending on the concrete case, the graph is slightly modified to allow classical min-cost flow algorithms to solve the problem efficiently. These modifications contain the introduction of a single main source and sink to model the flexibility of microgrids in $\mathscr{F}$ and the market, as well as costs on the arcs connecting the various microgrids with each other. These arc costs are defined in such a way, that trades between microgrids in $\mathscr{S}$ and $\mathscr{D}$ are preferred over any other trade. Furthermore, trades with microgrids in $\mathscr{F}$ are preferred over trades with the market m to ensure that in the resulting solution, the flexibility within the microgrids is first used up before increasing or decreasing the power exchange with the market.

The resulting solution of the min-cost flow problem specifies the trading between the various microgrids. In detail, the flow over an arc (i,j) can be seen as the power traded from microgrid i to microgrid j. Based on this solution, we can compute the power consumed or produced by each microgrid for time slice t, which then can directly be used as input for the power flow computation.

6.4.3 Grid Feasibility

Based on the solution of the previous step, we check whether the planned solution is also feasible w.r.t. the grid constraints. The algorithm is based on well-established power flow equations to compute the power flow on the lines of the grids. If these turn out to be infeasible, a repair algorithm adjusts the planned solution to reach grid feasibility.

Power Flow Computation

Due to the computational requirement, we make use of DC power flow equations (as already introduced in Section 6.3) to calculate the resulting power flow p_l^L for each line $l \in \mathscr{L}$ of the considered electricity grid. If for no line the corresponding thermal limit L_l^{max} is exceeded, we can implement the microgrid solution and proceed with step three (see Algorithm 3). If some line limits are violated, we need to adjust the device-feasible solution using a repair algorithm to achieve a grid-feasible solution.

Repair Algorithm

The main variables for the repair problem are additional trades between microgrids (i and j), denoted by $\Delta x_{i,j}$. In a first step, we need to determine the remaining device flexibility of each microgrid, which can be used for the additional trades. For microgrid i and time slice t,

$$l_i' = l_{i,t}^D - \hat{x}_{i,t}^D,$$

is the lower limit of flexibility, and

$$u_i' = u_{i,t}^D - \hat{x}_{i,t}^D,$$

is the upper limit of flexibility for additional trades, whereby $\hat{x}_{i,t}^D$ corresponds to the solution of the previous step. This leads to the following constraint for the repair problem:

$$l_i' \leq \sum_{j \in \mathscr{M}\mathscr{G}} \Delta x_{i,j} \leq u_i' \quad \forall i \in \mathscr{M}\mathscr{G} \cup \{m\}. \tag{6.31}$$

Hereby, index m denotes the market, for which we assume infinite upper and lower bounds. To ensure that the power traded from microgrid i to microgrid j equals the negative of what j receives from i, we add the constraint

$$\Delta x_{i,j} + \Delta x_{j,i} = 0 \quad \forall i, j \in \mathscr{M}\mathscr{G} \cup \{m\}. \tag{6.32}$$

Depending on the physical properties and the structure of the underlying electricity grid, the power flow between two microgrids does not necessarily take a single path but may spread among various paths, connecting the two microgrids [131]. To efficiently compute the impact of a trade on the power flow throughout the grid, we use PTDF [160], which approximate the change in power flow over a line given a change in power generation and consumption in certain nodes in the grid. The PTDF is closely related to the DC power flow equations and is independent of the actual power generation and demand of the microgrids. It only depends on the physical properties and the structure of the underlying electricity grid, and can thereby be computed upfront. Let $\varphi^l_{i,j}$ denote the PTDF for line l and a trade between microgrids i and j. Then the additional trades $\Delta x_{i,j}$ change the power flow on line l by:

$$\Delta p^L_l = 0.5 \sum_{i,j \in \mathcal{MG}} \varphi^l_{i,j} \Delta x_{i,j} \quad \forall l \in \mathcal{L}. \tag{6.33}$$

Note that the factor of 0.5 stems from the sum, where we count every trade twice (once from i to j and once from j to i). To ensure feasibility w.r.t. the line limits, we have to fulfill

$$-L^{max}_l \leq p^L_l + \Delta p^L_l \leq L^{max}_l \quad \forall l \in \mathcal{L}. \tag{6.34}$$

Constraints (6.31) and (6.32) define the set of device-feasible trades between microgrids, constraint (6.33) models the consequence of the additional trades w.r.t. the power flow, and constraint (6.34) further restricts the trades to ones, that result in a grid-feasible solution. Note that constraints (6.33) and (6.34) may also be merged into one set of constraints, in which Δp^L_l is not directly modeled.

The main objective of the repair problem is to ensure a grid-feasible solution, which is given by constraint (6.34). Hence, other, secondary, objectives may be added to decide which of the feasible solutions to choose. Within this work, we chose to reduce large additional trades as much as possible, which leads to the following objective:

$$\min \sum_{i,j \in \mathcal{MG}} (a_{i,j} \Delta x_{i,j})^2, \tag{6.35}$$

where $a_{i,j} > 0$ is an additional parameter that may indicate an ordering in preference over the additional trades, such as e.g., trades with the main grid being discouraged by a large a-value.

The resulting optimization problem is a quadratic optimization problem with linear constraints. Due to the positive a-values in the objective, the resulting matrix is positive definite. Coupled with the linear constraints, this problem can be solved efficiently with modern solvers. The resulting solution is composed of additional trades, which together with the device-feasible solution now build up the final solution, which is feasible w.r.t. device and grid constraints.

6.4.4 Parameter Updates

The updated solution of the repair algorithm respects all grid and device limits and can now be translated into control actions for the various devices within each microgrid. The achieved market and P2P solution specifies how much power has to be distributed among the households and devices of each microgrid. In the following, we present one possible way to distribute this among the devices of microgrid i.

Let $\bar{x}_i^D$ be the power assigned to microgrid i in the device and grid feasible solution for the current time slice. In a first step, each household within the microgrid receives its (inflexible) household load. We then subtract the sum of the household loads P_i^{HL} from the power assigned to the microgrid to determine the remaining power to be distributed among the remaining flexible microgrid and household assets. Let $\tilde{x}_i^D = \bar{x}_i^D - P_i^{HL}$ denote this remaining power. There are many ways how to distribute this remaining power among the flexible devices. In our case, we want to minimize PV curtailment and distribute the resulting power equally among all batteries and EVs subject to the device constraints. Therefore the problem can be seen as a resource allocation problem, for which efficient algorithms, such as the cave-filling algorithm exist [184]. The resulting solution is then used to distribute the power among the microgrid and household devices and to compute the new amount of energy in the various storage devices.

Another parameter, which may need to be updated is X_i, indicating the desired power to be bought (or sold) from the market. The main goal is to keep the power profile as flat as possible for each microgrid, while also trying to stay as close as possible to the day-ahead energy solution. Hence, we start with $X_i = (\tilde{x}_i^M / |\Delta\mathcal{T}|)\Delta t$, which corresponds to the power level of an equally spread day-ahead solution. Throughout the real-time control, deviations in market exchange from this desired level X_i may appear, and the value has to be adapted. The main idea in updating X_i is to equally spread the remaining amount of energy to exchange with the market among the remaining time slots. Let $X_{i,t-1}^M$ denote the total amount of energy exchanged with the market up to and including time slice $t-1$. Then, for time slice t, define the desired power level to be

$$X_i = \frac{\tilde{x}_i^M - X_{i,t-1}^M}{|\Delta\mathcal{T}| - t + 1}\Delta t. \tag{6.36}$$

Based on this distribution of power among the devices and the new target level X_i, the flexibility of the next time slice $t+1$ can be computed and implemented.

6.4.5 Extensions, Alternatives and Limitations

The introduced components of the three-step framework can be seen as the base approach, which may be further modified to better align the solutions with individual preferences or other requirements. In the following, we briefly present some possible extensions and alternative formulations.

Device Feasibility

While the initialization of the ideal power exchange with the market does not allow for many alternatives, the min-cost flow problem can easily be modified. In particular, the cost structure of the graph can be used to represent a number of different secondary objectives and preferences. However, it should be noted that the cost structure should still be in line with the hierarchical approach of trading, i.e. the cost of arcs connecting nodes in $\mathcal{S}$ and $\mathcal{D}$ should be lower than the cost of arcs incident to nodes in $\mathcal{F}$ and m. In addition, the costs of arcs incident to m should be the highest among all. Given these restrictions, possible extensions could encompass:

» Use the cost of arcs between microgrids to express some mutual preference between the microgrids. This could be due to similarity or the geographical distance between neighborhoods.

» Use the cost of arcs to express the willingness of a microgrid to participate in P2P trades and to use its flexibility. This may be of particular interest for microgrids in $\mathcal{F}$. Microgrids that are willing to trade their flexibility to help other microgrids may associate a very small additional cost with their incident arcs, while microgrids that prefer to keep their flexibility for future time slices may impose a larger additional weight.

» Use the cost of arcs to connect the min-cost flow problem with the underlying electricity grid. Each trade between microgrids has an impact on the outcome of the power flow computations by increasing and decreasing the demand at two points in the electricity grid. Assuming that these two points are close by in the grid, the affected part of the grid is rather small, leading to a higher probability of the flow still being feasible. Therefore, another idea is to use the costs of the arcs connecting the microgrids with each other to represent some distance measure on the underlying electricity grid. Thereby, trades within the same branch of the grid may be preferred.

Next to the cost structure of the arcs, the graph itself may also be used to represent limitations of the P2P trading scheme. Within the currently presented graph, all microgrids are connected to each other. An interesting idea is to restrict the arcs to better incorporate the underlying grid or communication structure. It should be noted that the assumption of a sufficient liquidity of the market implies the existence of a device feasible solution.

Grid Feasibility

Instead of using the DC power flow computation, which only approximates the physical properties of the underlying electricity grid, more accurate AC power flow computations could be used for the first computation. In recent years, new numerical solution techniques have been developed, which considerably speed up the AC power flow computation [82]. Therefore, even AC power flow computations may be employed to verify if line limits are respected.

The repair algorithm, which is based on a version of the DC power flow computation, may also be updated with more accuracy in mind. Techniques, such as the linearized DistFlow model [16], or other linearized AC power flow formulations [137, 150], may strike a good balance between accuracy and computational requirements.

In contrast to the device feasibility, the repair algorithm problem may be infeasible. Due to the strict requirements of achieving the planned SoC for each device at the end of the time slot, larger energy trades may be needed during later time slices. Coupled with uncertainty in PV production and household demand, these required trades may violate the grid constraints, leading to a situation, in which either the grid constraints are violated or the planned SoC of the devices are not achieved. To avoid such a situation, either a good forecast of the PV generation (see Section 6.5), or the option to drop the strict requirements on the SoC of the devices is needed.

Parameter Updates

Regarding the distribution of power among the various devices of a single microgrid, the proposed solution maximizes the PV usage and tries to allocate the remaining power equally among all batteries and EVs. However, there are other ways to distribute the power among the devices:

» A first approach is to use the target values of batteries and EVs as a reference for the distribution of the remaining power, instead of using the flexibility of the devices. Based on these values, the goal of the allocation could be to minimize the maximal deviation over all devices.

» A second approach focuses again on the flexibility of the devices. As mentioned in Section 6.3, the flexibility of the batteries and EVs depends on various aspects, whereby the initial energy at the beginning of the time slice is one of them. Therefore, the decision of how much power to use for the device in a time slice may have an impact on the flexibility of the device in the following time slice. Hence, we distribute the remaining power in such a way that the flexibility of the devices for the next time slice is maximized.

Finally, a very interesting decision is the update of the power exchange level X_i. As the main goal is to minimize fluctuations in the power exchange with the market, this value often does not change. However, using this parameter to decide how much to trade with the market at a certain time slice also allows the microgrids to participate in balancing markets. Thereby, microgrids could support grid operators with (local) imbalance regulations. Given an external signal, indicating whether there is a surplus of electricity or demand in the grid, the update of parameter X_i may be decreased or increased for a certain time window to contribute towards a balance between supply and demand. A number of different balancing markets exist to serve various types of flexibility, depending on the required timing. This may range from a few seconds for the primary response, to minutes or even hours for the secondary or tertiary response. It should be noted that both the timing as well as the required duration restrict the potential devices that may provide flexibility to a few types. While flywheels and batteries for example can react quickly to required changes in demand or supply, the duration is often rather limited. Changes in consumption pattern in industry on the other hand need a longer planning phase in the beginning, but can be sustained for multiple hours or even longer. Depending on the deviation from the originally desired power exchange level and the duration, the target values for the batteries and EVs may need to be adjusted to ensure a feasible solution for future time slices.

6.5 Numerical Study

In this section, we test and evaluate the proposed real-time control approach and analyze and discuss the numerical results achieved for multiple underlying grid structures. We first introduce and explain the used data in Section 6.5.1, before testing the above-presented algorithm in detail in Section 6.5.2. We use an adapted version of the microgrid model presented in Chapter 2 to obtain a day-ahead solution for a single 15-minute time slot. We then compare the results of the real-time approach to two other algorithms. The first one represents the case of a naive real-time control, whereby each device charges or discharges with its intended power level, and any surplus of PV is simply fed into the grid. The second algorithm represents the opposite and is an offline algorithm, that extends the system model (6.24)-(6.30) by considering all time slices at once and has access to the (aggregated) PV and household load data of each microgrid for the whole time horizon. Thereby, it serves as a lower bound on the possible objective values of the real-time control approach.

The algorithms are implemented in Python 3.9, and Gurobi 10.0 is used to solve the mathematical optimization models on a standard laptop with an Intel Core i5-8250U CPU and 8 GB RAM.

6.5.1 Data

The required data to test the proposed real-time algorithm can be split up into three parts: The electricity grid data, the microgrid data for the day-ahead operation problem, and the microgrid data for the real-time algorithm. Hereby, the electricity grid data directly determines the number and the sizes of the considered microgrids. Each microgrid is defined by a set of (aggregated) PV generation and household load profiles, as well as a communal battery and EVs.

Electricity Grid Data

To test and analyze the presented real-time control approach, we use some of the smaller Matpower grid examples, presented in [279]. Within these grids, the number of microgrids ranges from 3 to 41, while the total aggregated load is between 0.315 and 1.25 MW. Note, that in the original grid data, each grid

Name	buses	branches	MGs	size MGs	households	$\sum$ load
case9	9	9	3	100 - 138	349	0.315 MW
case14	14	20	11	3 - 104	283	0.259 MW
case57	57	80	41	1 - 418	1312	1.25 MW
caseNW	124	123	54	16 - 506	7091	6.407 MW

Table 6.1: Overview of tested grids, including the microgrid configuration.

had multiple buses producing electricity. Due to the structure of our real-time approach, we assume that only one of these buses serves as the connection to the grid. To also be able to test the real-time balancing algorithm for a larger number of microgrids and a higher load, we use the MV power distribution system as presented in [232]. This grid has a radial structure, which fits well with the assumption of having one connection to the electricity markets. The grid consists of 124 buses, and 123 branches, whereas not every bus is associated with a load. In total, there are 54 buses with a non-zero load, which correspond to the microgrids, and the aggregated load equals 6.407 MW. Further detailed information on this grid can be found in [232]. Table 6.1 provides an overview of the tested grids, including a summary of their microgrid configuration.

Day-Ahead Microgrid Data

As mentioned, each microgrid is associated with a specific bus in the electricity grid. In particular, the number of households within a microgrid directly relates to the load associated with the corresponding bus. We assume a peak average power consumption of 0.9 kW per household and 15-minute time slot. This results in microgrids consisting of 1 to 506 households for the various MV grids.

The households in a microgrid can be characterized by their (inflexible) demand profiles, their EVs with corresponding arrival and departure times and demands, as well as their PV systems. The same underlying data as used in Chapter 5 is used to obtain the day-ahead solutions.

Real-Time Microgrid Data

The power profiles of the household loads as well as the PV generation for the day-ahead operation are based on 15-minute time slots and represent the energy usage or generation during a time slot. In the real-time algorithm, on the other hand, we need a finer time granularity to know how the energy usage or generation spreads within the 15-minute time slots. For the PV generation, we use the data set published in [207], which offers a granularity of 1 second. Furthermore, in [249], 74 synthetic household demand profiles for a year with 1-second granularity are presented. For a single 15-minute time slot, we normalize these profiles and then scale them with the energy demand or generation of the time slot, for which we test the real-time algorithm.

6.5.2 Results and Analysis

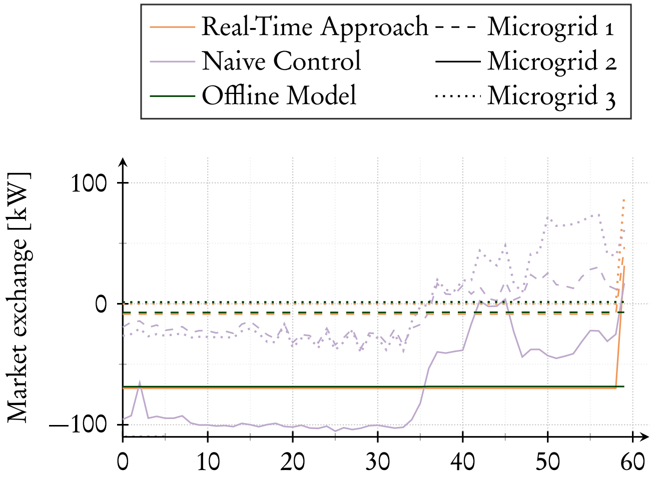
In the following, we present and analyze the results achieved by the real-time control algorithm in detail and compare them to the solutions of the naive control approach as well as the optimal offline model. We start with a comparison of the results of the three approaches and highlight the advantages and disadvantages of the real-time approach. We assume a perfect knowledge of all parameters on the day-ahead level for this first analysis. Afterward, we proceed with an analysis of how the three approaches can deal with uncertainty, before focusing on the computation times of the real-time approach.

Comparison to Benchmark Algorithms

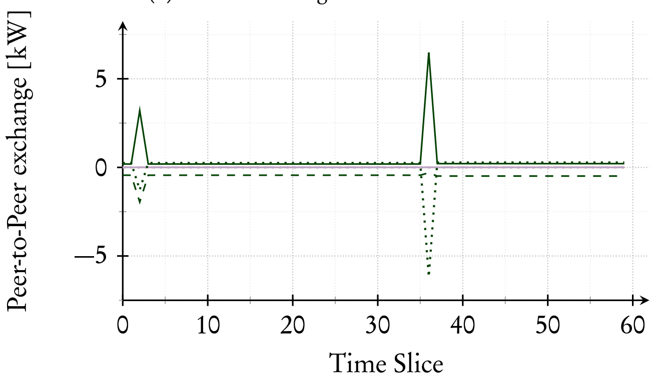
In the following, we present some first results for the individual microgrids of MV grid *case9* (see Table 6.1) for the three different algorithms (see Figure 6.2a). We first consider a time slice length of 15 seconds and present the market exchange of each microgrid as well as the aggregated P2P trading between the microgrids for each time slice for the whole time horizon of 15 minutes (see Figure 6.2b).

Comparing the market exchanges of the microgrids of the naive control with the optimal offline results highlights the need for a real-time control approach to minimize power fluctuations on an MV grid level (see Figure 6.2a). The fluctuations in the power profile of the naive control approach are caused by the short-term fluctuations and mismatch between the PV generation and the household loads. The offline model with its perfect knowledge on the other hand can react to these fluctuations by a clever scheduling of charging and discharging of batteries and EVs, which leads to a perfectly flat profile. The real-time control algorithm also aims to minimize these fluctuations and it achieves this goal for all but the last time slice, as can be seen in Figure 6.2a.

Similarly to the optimal offline model, the real-time algorithm also makes use of storage devices, such as the communal battery and the EVs. Hereby, it aims to supply power in time slices, where the PV generation and the ideal market exchange are not sufficient to cover the household demand and to store power in times when there is too much supply. However, these additional charging and discharging decisions cause a loss of energy due to the charging and discharging (in-)efficiencies, which was not accounted for in the day-ahead solution. To still ensure the demand-supply balance throughout the whole time slot, more energy than planned has to be bought for these approaches. The main difference between the real-time control and the offline model approach lies in the way the energy lost due to the inefficiency of batteries and EVs is bought. While the offline model can use its knowledge of the whole time horizon to evenly distribute the additional power among all time slices, the real-time control approach only realizes its shortcoming at the last time slice, leading to a sudden power peak, see Figure 6.2a. This also explains the small differences between the flat power profiles of the real-time approach and the optimal offline model.



(a) Power exchange with the market.



(b) Power exchange between microgrids.

Figure 6.2: Aggregated power exchange over time for microgrids 1, 2 and 3 for the three different approaches for electricity grid *case9* and $\Delta t = 15$ sec.

However, a simple increase of the parameter X_i to account for the energy loss may already counter this problem. It should also be noted, that the naive control approach does not suffer from this imbalance due to additional charging and discharging. However, as it simply feeds any PV surplus into the grid, it directly suffers from a highly fluctuating power exchange profile, which is also not desirable from a market point of view.

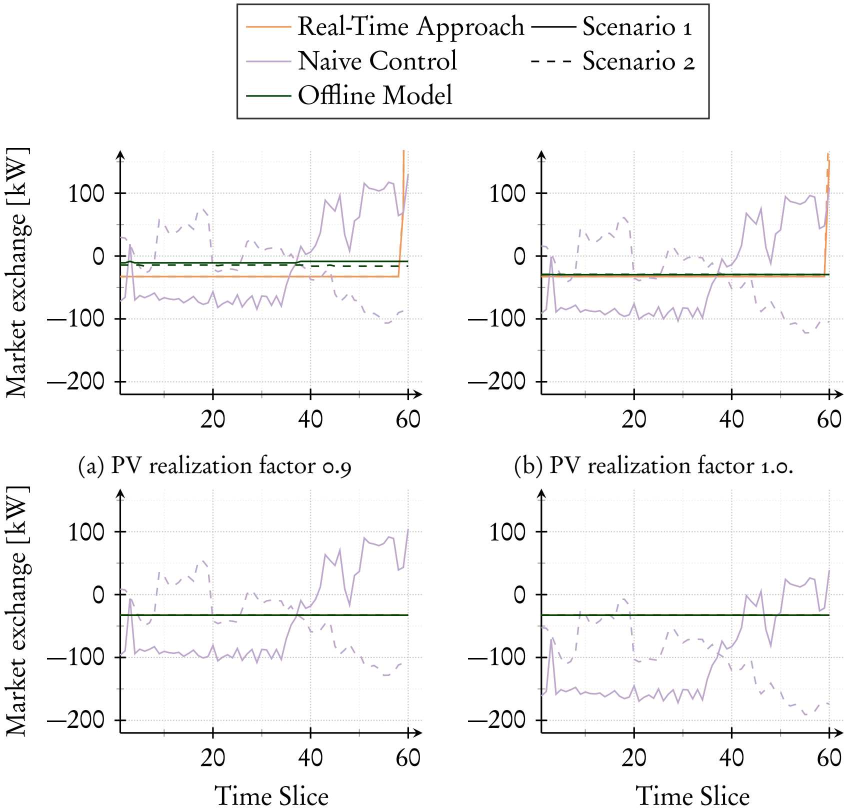
When focusing on the P2P exchange between microgrids, we notice that in this case, only the optimal offline model makes use of the option (see Figure 6.2b). In general, the real-time control approach only makes use of the P2P trading option when the device flexibility is not sufficient for some microgrids. The offline model, on the other hand, prefers to use P2P trading, as this minimizes the additional usage of storage devices, and thereby the unaccounted losses.

Impact of Uncertainty in PV and Household Forecasts

A similar problem to the unaccounted loss of energy may occur when considering the effect of uncertainty on the algorithms. In the following, we analyze the impact of uncertainty on the real-time control algorithm in detail. We differentiate between two types of uncertainty: The day-ahead uncertainty, which is represented by the uncertain total amount of energy needed by households or generated by PV systems for a specific time slot, and the real-time uncertainty, which reflects how the household loads or PV generation are spread within a time slot.

Starting with the day-ahead uncertainty, we focus mainly on the uncertain PV generation. In a small area, as represented by the considered MV grids, there is a high correlation between the realizations of PV generation. In contrast, we assume that the household load uncertainty is independent for each household. Therefore, even for the smallest grid with about 300 households (see Table 6.1) the individual uncertainty cancels out to a high degree. Hence, the prediction of the aggregated household load within a grid is quite accurate and we do not focus on this uncertainty during the analysis.

Figure 6.3 shows the outcome of the three approaches for various levels of PV uncertainty. Note that for Figures 6.3c and 6.3d the solution of the real-time approach and the offline model are the same, and therefore the line of the real-time approach is not visible. Figure 6.3b can be seen as an aggregated version of Figure 6.2a. Thereby, it supports the previous analysis and conclusions regarding the problem of additional storage usage even in the case of a perfect PV prediction. However, the problem gets even worse, when there is an overestimation of the PV generation in the day-ahead operation phase, as seen in Figure 6.3a. In that case, demand and supply are already out of balance over the whole time slot even without considering the unaccounted losses due to the additional usage of storage devices. The main problem with the current real-time control algorithm is that it only realizes this overestimation of the PV generation just before the last time slice. It then suddenly has to react to this information, leading to a large



(a) PV realization factor 0.9

(b) PV realization factor 1.0.

(c) PV realization factor 1.03.

(d) PV realization factor 1.4.

Figure 6.3: Aggregated power exchange with the market over time for the three different approaches for electricity grid *case9* and $\Delta t = 15$ sec and various levels of PV realization.

peak in consumption, which may even be grid-infeasible (see Figures 6.3a and 6.3b). It should be noted that the peaks differ considerably between Figures 6.3a and 6.3b. In the case of Figure 6.3b, only the energy lost due to the additional charging and discharging has to be bought. In Figure 6.3a, on the other hand, the peak additionally consists of the overestimated amount of PV generation, which is significantly larger than the energy lost due to the additional charging and discharging. An underestimation of the PV generation, on the other hand, can easily be dealt with. Even a small underestimation of the PV generation leads to a situation, in which the real-time control approach can use this additional generation to balance out the unaccounted energy loss (see Figure 6.3c), and thereby once again obtain an optimal solution. This also holds true for large underestimations, as can be seen in Figure 6.3d.

Summarizing, the results of the real-time approach strongly depend on the quality of the PV forecasts in the day-ahead stage, however, this is mainly one-sided. The algorithm encounters difficulties in finding a feasible solution when faced with an overestimation of the PV generation over the whole time slot, however, it can easily deal with an underestimation of the PV generation. This observation emphasizes the need to account for uncertainty in the day-ahead operation problem. A suitable candidate is (adaptive) robust optimization, as proposed in Chapter 5. Its focus on ensuring feasibility independent of the uncertainty realization often results in an underestimation of the actual PV generation, which aligns well with the working of the real-time control algorithm.

The second type of uncertainty, namely the real-time uncertainty, is already taken care of by the design of the real-time control algorithm. Due to the online nature of the algorithm, it makes decisions based only on the information from the past or the current time slice. Hence, it is independent of any forecast of future generation or demand. In Figure 6.3, the results for two different real-time uncertainty realizations are given. Scenario 1 corresponds to a realization, in which the PV generation has a peak in the beginning, while the aggregated household load has its peak towards the end of the time slot. This is a scenario, in which the oversupply of power in the early time slices can be used to charge batteries and EVs and use that stored energy at later time slices to cover for the higher demand. Scenario 2 is the opposite, it starts with a peak in demand and ends with a peak in PV generation. Theoretically, this should be a more complex setting for any approach, however, if the initial state of charge of EVs and batteries is sufficient, the approach is able to cover the early demand peak. Hence, the real-time approach is able to deal with real-time uncertainty to a large extent due to its online nature, which does not depend on any forecasts of demand or production.

Running Time and Scalability

Given the real-time nature of the proposed algorithm, its running time is of high importance to ensure that decisions can be made in time. To test and analyze the running time of the algorithm, we first theoretically analyze the running time of each individual component, presented in Section 6.4. The second part is composed of a numerical simulation, which supports the theoretical conclusions and shows the potential of the algorithm for a real-world implementation.

Following Algorithm 3, we have up to five computation steps per time slice:

» *Computation of device bounds*: Computing the device bounds only requires a few arithmetic calculations, which can be done efficiently. In addition, these calculations can be made in parallel for each microgrid and device, leading to a very fast computation. Note, that for the results presented in Table 6.2 and Figures 6.4 and 6.5 only the computations for the microgrids are run in parallel, while the computations for the devices within each microgrid are still run in sequence.

	case9		*case14*		*case57*		*caseNW*	
Δt	RTC	OA	RTC	OA	RTC	OA	RTC	OA
60	0.082	1.122	0.077	1.925	0.239	71.180	0.483	525.601
30	0.157	2.457	0.142	4.091	0.473	144.532	1.068	1099.56
15	0.330	6.528	0.309	9.037	0.968	298.101	2.002	2158.19
10	0.498	11.020	0.437	15.153	1.458	473.66	3.372	3492.01
5	0.996	38.708	0.925	46.152	3.036	-	6.395	-
1	5.310	-	5.046	-	16.723	-	33.012	-

Table 6.2: Total running time (in sec.) for the real-time control (RTC) approach and the offline approach (OA) for various time slice lengths (in sec.) and electricity grids. Entries with - did not terminate due to a shortage of memory.

- *Min-cost flow problem*: The min-cost flow problem only depends on the number of microgrids and is independent of the number of households and thereby the size of the microgrids. Even in large MV grids, the number of microgrids is usually relatively small. Therefore, this problem can be solved efficiently, using either an LP formulation or well-known strongly polynomial algorithms (see e.g., [200, 244]).
- *Calculation of power flow*: Given the focus on DC power flow equations, the calculation can be reduced to a simple matrix-vector multiplication. The size of the matrix (respectively the vector) depends on the number of lines and buses in the electricity grid. It is possible to further speed up the computation by ignoring the buses, which are not connected to microgrids.
- *Repair algorithm*: In its current form, the repair algorithm is modeled as an LP with a quadratic objective function. Given suitably chosen weights in the objective function, it is well known that such problems can be solved in weakly polynomial time [135]. Once again, the size of the resulting mathematical model only depends on the number of microgrids as well as the number of lines within the grid and thereby should be rather small compared to the number of devices or households.
- *Parameter update*: The parameter update, as presented in Section 6.4.4, can be done in parallel for each microgrid. Within each microgrid, the cave-filling problem can be solved in linear time on the number of devices [185]. The computation of the parameter X_i is a simple numerical calculation following equation (6.36).

Table 6.2 and Figures 6.4 and 6.5 show the running times of the real-time control approach for various time slice lengths and grids. Hereby, Table 6.2 compares the total running times of the real-time control algorithm and the offline model approach, while Figure 6.4 focuses on the average running time per time slice of only the real-time control algorithm. Figure 6.5 shows for a time slice length Δt of one second some additional statistics on the running time per time slice beyond the average value.

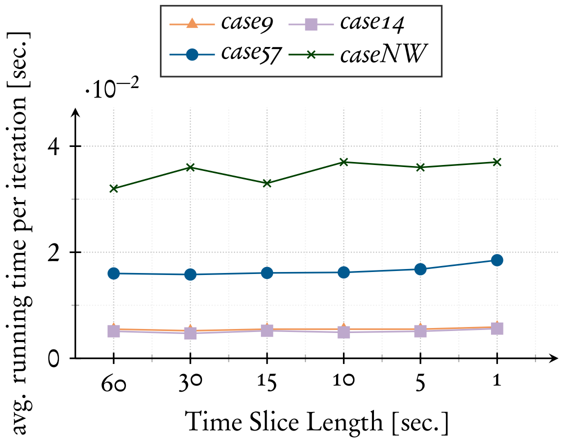


Figure 6.4: Average running time per iteration (in sec.) of the real-time control approach for the four different electricity grids.

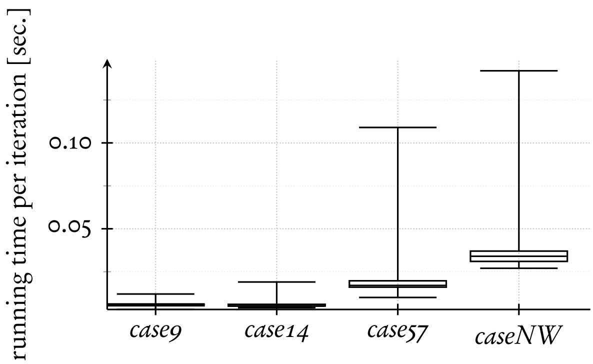


Figure 6.5: Boxplot statistics on the running time per time slice for various grid types for a time slice length of 1 second.

Comparing the real-time control algorithm with the offline model, we notice that the real-time control algorithm scales much better with the number of time slices, respectively the time slice length (see Table 6.2). Figure 6.4 supports this conclusion in that the running time per time slice is nearly constant for all grids. The running time of the offline model on the other hand does not follow such a clear linear trend for smaller time slices and instances with a very large number of time slices often cannot be solved due to a shortage of memory. In addition, even instances that are solvable need 14 to 1000 times more computation time compared to the real-time control approach.

In general, the running time of the real-time control algorithm per time slice mainly depends on the number of microgrids and the corresponding number of households per microgrid, but is nearly independent of the time slice length (see Figure 6.4). This insight supports the theoretical analysis of the individual components, in which the running time of the components depends on either the number of microgrids, the number of devices per microgrid, or the size of the underlying electricity grid. However, the running time of an individual time slice may also be affected by which components are used. As shown in Algorithm 3, not every component is always used. Both, the min-cost flow problem as well as the repair algorithm are only run if either the device flexibility of microgrids is not sufficient or the resulting solution violates branch limits. These cases mostly do not show up, leading to very low computation times in the vast majority of iterations (see Figure 6.5), although outliers may appear. Nevertheless, even these outliers are small enough for the algorithm to be employed in a real-time setting. It should be noted that the overhead due to communication has not been considered and must be added to the running times in case of a real-world implementation.

6.6 Discussion and Conclusion

This chapter aims to design a grid-aware real-time control algorithm, which uses the decisions made at the day-ahead market to guide its real-time actions. We created a three-step framework, which allows a set of microgrids to jointly control their balancing actions to maintain a flat power exchange profile with the electricity market. The framework is built up of multiple separate components, which can be set up according to individual preferences or computational requirements. Due to an aggregation step at the microgrid level, privacy-relevant information and data are not shared outside the microgrid, which may increase the acceptance for real-world employment. A case study on multiple MV grids shows promising results w.r.t. the running time and the objective of the algorithm. A comparison to an optimal offline model revealed that given some light assumptions, the real-time control approach obtained an optimal solution in most cases.

The comparison to the naive control strategy, in which all devices simply act according to their planned power levels, also highlights the importance of having a real-time control approach to implement the day-ahead solution in a predictable manner. In particular, it is not desirable from a market perspective to not have any control within the 15-minute time slots. Due to the increased share of non-renewable energy sources as well as the increased load due to EVs or heat pumps, the mismatch between demand and supply leads to highly fluctuating power profiles, which may also synchronize within a region. This situation calls for a control approach, which can deal with the imbalance in demand and supply in real-time. Our proposed algorithm solves this imbalance on three different layers. In the first layer, each microgrid uses the flexibility of its own devices to ensure a balance. If this local mechanism is not sufficient, the second layer enables microgrids to trade with each other. Thereby, neighboring microgrids can help each other with their remaining flexibility on a regional level. In the third level, microgrids can increase or decrease their power exchange with the market to temporarily deal with the remaining demand or supply. This hierarchical structure increases the self-consumption of renewable energy generation within microgrids and promotes the trading between neighboring microgrids. The advantages of these incentives are the reduced usage of the electricity grid and the connection of producers and consumers on a local level.

The analysis also revealed another interesting aspect in the interplay between day-ahead operation and real-time control approaches, which is often neglected or ignored. Implementing the planned (average) power exchange level with the market throughout the whole time slot often requires the usage of storage devices such as batteries beyond the planned day-ahead usage. Assuming imperfect batteries, losses due to the additional charging and discharging, may disrupt the planned demand-supply balance. There are two levels, where this issue can be addressed. In the real-time layer, the additional demand (to cover the losses) may be realized by increasing the target power exchange level slightly. However, this may directly lead to an imbalance in the markets, in case every microgrid requires more power than planned. The second option is to account for the losses due to real-time balancing already in the day-ahead operation problem. This avoids the problem of increasing the actual load of every microgrid during the real-time control and decreases the deviation in the demand-supply balance.

Based on the achieved results and interesting insights, various interesting research directions arise. In a first step, a more detailed study on the interplay between day-ahead operation and real-time control approaches is necessary to explore and evaluate the different options to deal with the additional battery usage and its accompanying energy losses. In Section 6.4.5, a short overview of possible extensions and alternatives to the proposed components is provided. A further study of their performance in the three-step framework could produce interesting and valuable insights beyond our analysis. A last research direction may focus on the implemented components of the framework. Due to the real-time aspect of this algorithm, the running time of each component is of high importance, and tailor-made algorithms may further speed up the overall computation time.

7 Conclusion

Abstract – *In this chapter, the main results of this thesis are briefly summarized. Afterward, the research questions introduced in Chapter 1 and the corresponding contributions are reviewed. This thesis is finally concluded with recommendations for future work.*

7.1 Summary

The energy transition is currently transforming our energy system at an increasingly rapid pace by decarbonizing the electricity generation and electrifying various aspects of everyday life at the same time. These drastic changes are creating new challenges and problems, which need to be solved to ensure a stable electricity system in the future. One promising approach to tackle these problems is to activate the flexibility of residential devices by encouraging households to participate in local energy trading and market approaches. In this thesis, we have reviewed and analyzed various aspects of local energy trading and proposed several approaches to deal with important, but often neglected aspects.

In Chapter 2, we explained the concept of a microgrid, which is a set of households connected via the electricity grid, that jointly manage their energy consumption and production. We introduced the different participants and entities, including the various devices, such as PV systems, electric vehicles (EV), or batteries, and based on this presented a mathematical formulation of the flexibility offered by a microgrid. We concluded this chapter with a short overview of solution techniques, which have successfully been applied to solve a wide range of local energy trading problems.

In Chapter 3, we provided an overview of the current state of the literature on the topic of local energy trading. Due to the wide range of approaches and settings, we first structured the relevant literature by means of a classification scheme, focusing on various characteristics of local energy trading approaches, such as the objective, the participants, or the way flexibility may be used. We identified three main research directions, which differ in their considered setting and objective. Beyond these clusters, we have identified three aspects, which to a large extent have been neglected in the reviewed literature. These three aspects formed the base for the following chapters.

In Chapter 4, we addressed the first aspect, namely the modeling and analysis of human behavior and its impact on local energy trading and markets. We reviewed different behavioral models from social science and then translated the ABC model into a mathematical optimization model, whose structure resembles a multi-objective optimization model. In a case study, we first analyzed the resulting bidcurves of a single household from a multi-objective perspective, and based on this performed a sensitivity analysis on the parameter choices for a set of households participating in a local electricity market.

In Chapter 5, we proposed and evaluated two approaches dealing with uncertainty in data and forecasts in a day-ahead management and trading problem for a microgrid. The first approach was based on the technique of linear decision rules (LDR) as used in robust optimization. The corresponding analysis focused mainly on the underlying mathematical technique and its advantages and disadvantages. The second approach combined static robust optimization with a rolling horizon framework, which due to the repetitive re-optimization steps of the rolling horizon allows to react to updated forecasts and observed realizations of uncertainty. In a case study, we compared the impact of the individual uncertainty sources on the objective value and concluded that in particular, taking into account the time-dependent PV uncertainty contributes to an improvement in the objective value. Based on these insights, we generalized the rolling horizon framework by allowing more flexible starting time slots. To use the additional flexibility, we developed a tailor-made scheduling tool, which identifies promising starting time slots for the iterations of the rolling horizon. In a case study, we demonstrated the potential of this approach and developed it further by means of an online version of the generalized rolling horizon framework, which enabled a reaction to unusual good or bad forecasts and observations by means of an online scheduling tool. In a second case study, we showed its potential and also reflected on its disadvantages.

In Chapter 6, we addressed the third aspect, focusing on grid constraints in the context of a real-time control and balancing approach for a set of microgrids. In order to realize the day-ahead market solutions, we proposed a three-step framework, which uses the day-ahead solution as guidance for its online decisions. The goal of the approach was to realize the planned day-ahead solution as close as possible, by using flexibility first locally within a microgrid, then regionally by means of trades between microgrids, and finally nationally on the balancing markets. As each of these decisions impacts the connecting MV grid, special focus was placed on the grid constraints in the form of a DC power flow formulation. In a case study, we showed the potential of the proposed framework, focusing on the objective function and the computational time.

7.2 Research Question and Contributions

We conclude this thesis by coming back to the research questions posed in Chapter 1. The first research question

> *RQ1: Given the current state of local energy trading approaches, what aspects are missing or neglected?*

has been addressed in Chapter 3. We identified the following three aspects:

» The first neglected aspect is the modeling and integration of human behavior into local energy trading approaches. Even though the participation of individual households in electricity markets and similar trading approaches introduces the (sometimes) irrational behavior and decisions of humans, this aspect has been neglected in large parts of the reviewed literature. To some extent, this can be explained due to the complexity of understanding and modeling even simple human decisions. So far, this challenge has often been mitigated by assuming rational agents, which focus on one objective and by that significantly eases the analysis of equilibria and convergence results.

» The second aspect that mostly has been neglected is the uncertainty in data. Considering possible deviations in forecasts and predictions is of great importance, in particular for energy trading over longer time horizons. PV forecasts, for example, are known to decrease in accuracy, the longer the time between making the forecast and the actual realization. However, even approaches that focus on day-ahead energy trading often assume perfect knowledge of all parameters, which carries a high risk of leading to situations, in which the planned solution is not feasible.

» The last missing aspect is the integration of grid constraints in local energy trading. Modeling the physical power flow is known to be challenging, and thus separating the trading of energy between households from their impact on the grid results in far simpler models and formulations, for which it is often possible to derive analytical solutions or prove convergence of (decentralized) techniques. However, the increasing loads (in residential areas) already today burden the distribution grid and as electrification continues, this problem will become even more frequent and severe.

The second research question

> *RQ2: How can these aspects be addressed?*

has been split into three subquestions.

> *RQ2.1: How can we model human behavior and evaluate its impact on the outcome of local energy trading?*

We answered this first subquestion in Chapter 4 by combining the ABC model with mathematical (multi-objective) optimization techniques to allow households to input their preferred settings and motives into the decision-making process. The analysis showed two interesting results:

- On an individual household level, it is possible to partially confirm the key claim of the ABC model, which states that extreme external factors dominate internal motives when creating the behavior. In turn, this implies that internal motives have a larger influence when the external factors are rather neutral. Translated to the setting of modeling behavior in a local electricity market, this implies that the access to devices and additional information, such as prices or CO_2 emissions, is of great importance when analyzing the impact of the internal motives and preferences on the resulting bidcurves, and thereby on the market. Hence, considering human behavior and its impact on local energy trading and market approaches is important. However, this can only be done if households have access to sufficient flexibility in the form of various devices, such as e.g., batteries, heat pumps, or electric vehicles (EV). Without these devices, only a small fraction of the household load may change depending on the internal motives. Compared to the electricity consumption of the new devices, the change in the household load has only a very small impact.
- Looking beyond the individual household view and focusing on the outcome of the market, we have shown that some internal motives may lead to undesirable market results. However, these problems mostly appear for motives directly opposing the steering signals of the market. In such cases, the price, which serves as the steering signal of the market, cannot fulfill the goal of steering the decisions of the households into a feasible region. This misalignment between the motives and the steering signal can pose problems on two levels. First, it may lead to undesirable individual results w.r.t. the objectives of the households. The second identified problem takes place on the grid level, where grid constraints may be violated. Based on these observations, we discussed implications for the design of future local electricity markets and home energy management systems to avoid such a misalignment.

RQ2.2: How can we deal with uncertainty in data and forecasts?

We answered the second subquestion in Chapter 5 by testing and analyzing two techniques from robust optimization, which fit well with the conservative and careful management and regulation of the electricity system. We proposed two approaches, whereby the first approach focused on the linear decision rule technique itself. We showed promising results, but also shed light on some disadvantages. The second approach focused on the combination of a rolling horizon framework and (static) robust optimization. A case study showed significant improvements, which at first glance seemed counterintuitive to the expectations of a rolling horizon implementation. A detailed analysis of the impact of the uncertainty sources individually on the objective value revealed that the observed improvements are based on only two of the considered uncertainties: The EV demand and the PV generation, which are both sensitive to time:

» The EV demand is reflected in the state of the battery of the EV, and therefore, observing the state of charge of the EV after it arrives allows to derive the demand realization. Based on how the robust optimization works, we can assume that in general there is more energy in the battery than in the worst-case scenario, which we prepared for. Therefore, we can adapt our future decisions to this surplus of energy in the EV in the case that a new re-optimization iteration is started when an EV is present.

» The PV uncertainty is even more time-critical. PV forecasts for a given time slot may differ in their predicted values, depending on the time they are made. We assume that the uncertainty and thereby the confidence interval decreases the closer the forecast is made to the actual realization of the PV generation, and therefore, PV uncertainty sets for a given time slot constantly change over time.

This led us to the main insight of this chapter, namely that the point in time when a decision is made is of high importance in dynamic environments under uncertainty and has a significant impact on the resulting solution.

Based on this insight, the main contribution of this chapter is the generalization of the rolling horizon framework to allow for a more flexible scheduling of the starting time slots of the iterations of the rolling horizon. We proposed two approaches, an offline and an online scheduling approach. Both showed significant improvements over the classical rolling horizon scheme, with reductions in costs of up to 85%. The advantage of the online scheduling approach over the offline version lies in its ability to react to unusual good or bad observations of uncertainty or forecasts, while the offline approach makes better use of the number of iterations over the time horizon. Both approaches are directly based on the main insight of the timing of decision-making and are thereby able to significantly improve the solution quality without (much) additional computational resources.

> *RQ2.3: How can we ensure that local energy trading approaches are grid-feasible?*

We answered the third subquestion in Chapter 6 by integrating grid constraints into a real-time control approach for a set of microgrids. Due to the ongoing electrification and increasing PV installations at a household level, the current distribution grid is already approaching its capacity limit, which hinders and delays the ongoing energy transition. Therefore, we focused on the limitations and constraints of the (MV) distribution grid connecting microgrids with each other. The key contribution lies within the development of a modular three-step control algorithm, which aims to implement day-ahead and intraday solutions in a real-time fashion. Its modularity allows for an easy adaptation to other settings, such as the control within a single microgrid. Thereby, grid constraints may also be introduced to P2P trading approaches between households within a microgrid.

The analysis of the proposed three-step algorithm highlighted the need for a real-time control approach to ensure grid feasibility. Due to short-term fluctuations in household demand and PV generation, the resulting power flows often exceeded the planned day-ahead and intraday solutions by a large margin in the case of no real-time control. Thereby, also grid capacity limits may be violated. The case study showed that the proposed real-time approach performs near-optimal under some mild assumptions on the PV forecasts. In addition, we observed that the additional required charging and discharging of storage devices, such as batteries or EVs, could lead to an unaccounted loss of energy, which should already be considered during the day-ahead or intraday operation phase.

7.3 Recommendations for Future Work

Within this thesis, we provided answers to the research questions by proposing and analyzing several algorithms, each focusing on a different aspect of local energy trading. During our work, we have identified several open research directions and opportunities to further develop and improve the proposed algorithms and case studies.

In Chapter 4, we have proposed an optimization model, which translates the internal valuation, motives and preferences of a household into input parameters. Within the case study focusing on the local electricity market, we did a sensitivity analysis of these input parameters. Hereby, we assumed that each household has the same motive weights, and drew conclusions accordingly. However, in an actual neighborhood, the assumption that all households have the same motive weights seems unrealistic, which indicates a possibility for future research to carry out the sensitivity analysis also for varying motive weights among the households. Comparing the results could then provide insights into the effect of the synchronization of motive weights.

Viewing the problem from a social science perspective, a second research direction could be to identify more realistic motive weights by a systematic survey of neighborhoods with different socio-economic backgrounds. A similar direction would be to analyze the effect of (bidcurve) recommendations of the home energy management system on the actual behavior of households. Hereby, an interesting question to be investigated is how additional information, such as the expected CO_2 emissions, costs, or state of charge of the EV, affects the choice of motive weights of prosumers.

In Chapter 5, we have proposed a generalized rolling horizon framework and presented two ways how the additional flexibility of choosing the starting time for the iterations can result in significant improvements. However, we have also identified shortcomings of both approaches. To overcome these disadvantages, a future research direction could be to combine the two approaches. This could result in a more predictable schedule of starting times of the iterations, which still allows to react to unusually good or bad forecasts and observations of uncertainty. Another idea is to replace the static robust optimization technique in the iterations of the rolling horizon with the linear decision rule model proposed earlier. Using the ability of the linear decision rules to react to uncertainty realization, we may be able to reduce the number of iterations without compromising on the objective value. Another interesting line of research is to analyze how the generalized rolling horizon framework can be combined with other uncertainty-based solution techniques, such as stochastic programming.

In Chapter 6, we have proposed a modular three-step framework, which ensures device and grid feasibility in a real-time control setting. Hereby, the focus of the grid constraints lay on the MV distribution grid, connecting the microgrids with each other and the market. However, the electricity grid of the individual microgrids has not been considered, which may be of interest for future work. A promising approach to including the LV grid into the framework is by including the constraints already at the computation of the microgrid flexibility. Instead of just aggregating all device flexibility, one could use the radial structure of the LV grid to cleverly aggregate the device flexibility while already taking the grid limitations into account. Another future research direction is to implement and test other power flow formulations, such as the linearized DistFlow model or the AC power flow formulation. If the focus continues to be on the proposed DC formulation, a tailor-made repair algorithm would be of interest. Hereby, a geometrical perspective may lead to efficient algorithms.

To put this thesis into context, we conclude with an outlook and a personal note on the energy transition in general. In my opinion, the energy transition can be broken down into three crucial key elements: The first aspect is responsible for and concerned with the design and development of the technologies needed to decarbonize the electricity generation and electrify carbon-based processes and aspects of society. In this area, we have already seen great progress over the last few decades in improving the efficiency of PV systems, wind power plants, batteries, and heat pumps. The second aspect deals with ways how these new technologies can be implemented into the energy system. Meeting the challenges associated with these major changes will require new ways of managing supply and demand through energy management and trading approaches. This is a rapidly maturing cornerstone that this thesis aimed to contribute to. The last inevitable step is to walk the talk and substitute fossil fuels with sustainable and renewable energy sources, which can produce enough of the required electricity for the next generations. Unlike the previous two aspects, this last element does not depend on the uncertain duration of research and development but relies on the efforts of policymakers and industry to push for the rapid employment of these new technologies and algorithms. However, as has become increasingly clear during the last years, it is not only politics and industry that influence the decision-making process on the use of these technologies. Individuals can and should also contribute to this ongoing discussion and act responsibly in the scope of their possibilities, such as in their voting choices, their choice of energy supplier, or their own daily consumption patterns. The energy transition is a highly complex challenge that can only be successfully managed if all stakeholders involved - research, policy, industry and society - understand the urgency and are committed to making a real change.

Acronyms

A	ABC	Attitude-Behavior-Context
	ADMM	Alternating Direction Method of Multipliers
	AR	Average-Realizations
C	C+I	Consensus and Innovation
D	DSO	Distribution System Operator
E	EMS	energy management system
	EV	electric vehicle
G	GNE	generalized Nash equilibrium
H	HEMS	home energy management system
	HP	heat pump
	HR	Historical-Realizations
	HV	high-voltage
K	KKT	Karush-Kuhn-Tucker
L	LDR	linear decision rule
	LEM	local electricity market
	LP	linear programming
	LV	low-voltage
M	MGO	microgrid operator
	MV	medium-voltage
N	NE	Nash equilibrium
P	P2P	peer-to-peer
	PEB	pro-environmental behavior
	PR	Partial-Realizations
	PTDF	power transmission distribution factor
	PV	photovoltaic
R	RCT	Rational Choice Theory
	RES	renewable energy sources
	RMSD	root-mean-square differences
S	SoC	state-of-charge
T	TSO	Transmission System Operator

V	VBNT	Value Belief Norm Theory
	VCG	Vickrey-Clarke-Groves

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List of Publications

[JH:1] J. Hönen, J. L. Hurink, and B. Zwart. A classification scheme for local energy trading. *OR Spectr.*, 45(1):85–118, oct 2022. ISSN 0171-6468. doi: https://doi.org/10.1007/s00291-022-00697-6.

[JH:2] J. Hönen, S. C. Doumen, P. H. Nguyen, J. L. Hurink, B. Zwart, and K. Kok. Modeling and analyzing the effect of human preferences on a local electricity market. *IEEE Transactions on Energy Markets, Policy and Regulation*, 2023. Under review.

[JH:3] J. Hönen, J. L. Hurink, and B. Zwart. Dynamic rolling horizon-based robust energy management for microgrids under uncertainty. *ArXiv*, 2023. doi: https://doi.org/10.48550/arXiv.2307.05154. Under review in *Sustainable Energy, Grid and Networks (SEGAN)*.

[JH:4] J. Hönen, J. L. Hurink, and B. Zwart. Threshold-based algorithms for an online rolling horizon framework under uncertainty – with an application to energy management. *ArXiv*, 2023. doi: https://doi.org/10.48550/arXiv.2311.11307.

[JH:5] J. Hönen, J. L. Hurink, and B. Zwart. Grid-aware real-time control and balancing between microgrids. *ArXiv*, 2023. doi: https://doi.org/10.48550/arXiv.2311.11294.

[JH:6] J. Hönen, J. L. Hurink, and B. Zwart. Robust energy management for a microgrid. In *2022 IEEE 7th International Energy Conference (ENERGYCON)*, pages 1–6, 2022. doi: https://doi.org/10.1109/ENERGYCON53164.2022.9830301.

[JH:7] B. Nijenhuis, S. C. Doumen, J. Hönen, and G. Hoogsteen. Using mobility data and agent-based models to generate future e-mobility charging demand patterns. In *CIRED Porto Workshop 2022: E-mobility and power distribution systems*, volume 2022, pages 214–218, 2022. doi: https://doi.org/10.1049/icp.2022.0697.

[JH:8] S. C. Doumen, J. Hönen, P. H. Nguyen, J. L. Hurink, B. Zwart, and K. Kok. Modeling and demonstrating the effect of human decisions on the distribution grid. In *2023 IEEE PES Innovative Smart Grid Technologies Conference (ISGT)*, pages 1–5, 2023. doi: https://doi.org/10.1109/ISGT51731.2023.10066376.

Jens Hönen is the main author for all listed publications, except for [JH:8] and [JH:2], where the main authorship is shared with S.C. Doumen and [JH:7], where the main authorship is shared with B. Nijenhuis and S.C. Doumen.

This thesis

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Propositions

accompanying the Ph.D. thesis

Local Energy Trading for Microgrids

Modeling Human Behavior, Uncertainty and Grid Constraints

by Jens Hönen,
to be defended on Thursday, March 28, 2024

1 — A good overview of a research topic is both useful and necessary, but can also be distracting for future research.

2 — A cooperation of people from many different areas is needed to tackle the energy transition.

3 — Not only the method but also the timing is important when making decisions.

4 — Unexpected insights and observations are often more relevant than the anticipated main result of research.

5 — Academic success is the result of the accumulation of past failures.

6 — Peer review is the least bad option to ensure high quality of publications.

7 — Poster sessions are more fruitful than presentation sessions for both presenter and audience.

8 — Creativity needs boredom.

9 — A more neutral and fact-based messaging and communication enables a more realistic and better perspective of our surroundings.

10 — Progress is the realisation of Utopias. *(Oscar Wilde)*