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Bachelorarbeit

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Strategien zur Optimierung des Betriebs einer flexiblen Energieressource am Energie- und Regelenergiemarkt

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Thema der Arbeit

Strategien zur Optimierung des Betriebs einer flexiblen Energieressource am Energie- und Regelenergiemarkt

Stichworte

DER, Optimierung, Flexibiliesierung, Vermarktung, Energiemarkt, Regelenergiemarkt

Kurzzusammenfassung

Diese Arbeit beschreibt eine Softwareoptimierung und darauf aufbauende Simulation, um die möglichen Kostensenkungen durch eine Flexibilisierung von Energieverbrauchern abzuschätzen. Verschiedene Szenarien demonstrieren Einsparungen von 10 - 60 % auf dem Spotmarkt. Auch das Prinzip der Bereitstellung von Ausgleichsenergie innerhalb eines Bilanzkreises durch flexible Verbraucher wird vorgestellt und analysiert.

Hendrik Obelöer

Title of Thesis

Strategeis for Optimising the Operation of a Flexible Energy Resource for Energy and Imbalance Markets

Keywords

DER, Optimisation, Flexibilisation, Marketing, Energy Markt, Imbalance Market

Abstract

This paper describes a software optimisation and subsequent simulation in order to assess possible energy cost savings in flexible consumers. Various scenarios demonstrate savings of 10 - 60 % on spot markets. The innovative principle of providing balancing energy to small and private control groups via these systems is presented and analysed.

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1 Introduction

The large scale introduction of renewable energies to electrical grids has already changed energy markets decisively. Where previously large power plants dominated the market, the uncontrollable nature of renewable energy resources has made prices much more volatile.

This raises the question to what extent energy consumers can react to such fluctuation via price signals. The overall impact of flexibilities on energy prices and the proliferation of renewable energies has been described in numerous studies. Many types of energy consumption or generation could be made more flexible which would in turn decrease grid congestion during peak hours and lower energy prices.

However, traditionally the transition to a flexible consumption of energy was not considered profitable for small and distributed resources. Taking into account the changes in energy prices and the possibilities of modern technologies, this calculation must be reassessed. This paper adds a further perspective to this topic. It describes a methodology and a software implementation for simulating possible savings in energy costs by introducing storage capabilities to energy consumers, such as power-to-heat systems.

This simulation is used to optimise the scheduling of energy consumption according to market prices and compare the potential savings of different technical configurations, i.e. varying the storage size and charging power. Moreover, the analysis of different marketing approaches reveals the benefits of leveraging short-term flexibilities for arbitrage trading. Under the modelled assumptions, energy costs can be more than halved for very flexible configurations. Even with small storage solutions the optimisation reduces costs by more than 10 %.

By flexibly scheduling a power resource, the simulation also allows to assess a novel approach in relation to grid stability. Control groups of renewable energies will often deviate from their market position because of forecast errors. A flexible resource might not conform to the traditional requirements for balancing energy, but it could still be integrated in a private control group, react in real time with the opposite deviation and thus minimise the imbalance of the control group. This paper describes how such an approach could be implemented and makes an estimate for the additional energy costs from the point of view of the flexibility operator. It is shown that the potential costs of this approach highly depend on market conditions.

Chapter 2 gives an overview over the technical and legal background while also describing the current state of research. Chapter 3 follows this up by outlining how the research questions could be answered and which requirements any simulation must fulfil. Chapter 4 explains how these requirements are fulfilled by the simulation and which design decisions were taken in developing the algorithm. Chapter 5 presents an analysis of various simulations. Chapters 6 and 7 sum up the results and findings and show where further research could build on the findings. The appendix includes further data from the analysis and a manual for using the developed software library.

2 Motivation and Background

A flexible energy resource can use its properties for two purposes: By responding to price signals, which are a reflection of supply and demand, energy costs can be significantly reduced. Likewise, the flexibility can be used to react to grid imbalances as they occur. Both aspects make the operation of energy grids more efficient and better tuned for high renewable energy penetration. These aspects have been the subject of extensive research. In order to fully understand the current possibilities and limitations of deploying flexible energy resources, this chapter will present an overview of the current research and examine remaining questions. This will be the starting point for defining and developing an appropriate simulation.

2.1 Minimising Costs

Flexible energy resources can be divided into three fields: flexible production (e.g. biogas), flexible consumption (e.g. power to heat), and a combination of these aspects (e.g. batteries). All these models can use their flexibility to decrease costs or respectively increase profits by aligning themselves with market prices. Moreover, restricting one's own energy consumption during times of high load could further reduce overall costs by minimising grid charges.

From the point of view of the grid or energy market, it is unimportant and even impossible to know whether these systems possess any kind of actual physical storage. The flexibility is expressed in how dynamic a system can react to price and control signals. This paper will focus exclusively on flexible consumers.

Villar, Bessa and Matos review currently discussed flexibility products and markets while also reporting on ongoing discussions and design ideas [1]. McPherson and Tahseen augment this research by analysing the effect of different market regimes and electricity system configurations on the profitability of storage assets [2]. In [3] and [4] the authors give insight in how an aggregator can combine various energy resources and use innovative market designs to increase the penetration of renewable generation.

Nowadays, many inflexible energy consumers are not managed with respect to fluctuating energy prices and therefore represent a large opportunity. The use of such flexibilities has been modelled in a range of studies. [5] and [6] demonstrate approaches to model home units as a combined flexible energy consumer.

In the case of [7], a more technical aspect of how to effectively combine, efficiently schedule and estimate prices for a diverse set of flexibilities is given. In [8] and [9] the authors optimise a PV operation on buildings with flexible consumers and storage options.

2.2 Offering Auxiliary Services

Selling power from renewable energy resources is a complex business. Especially when looking at wind and solar, which depend on weather factors, their energy production is seldom controlled. As a consequence, such portfolios tend to be exposed to imbalance prices.

Already in 2002, this problem was anticipated and Bathurst, Weatherill and Strbac presented an algorithm to determine the optimal market positions for a wind portfolio while keeping in mind the inaccuracies of the forecast. However, the imbalance price is only published after the fact and the imbalance amount typically reflects errors in forecasts which are typically supplied by third parties. As a consequence, a marketer might perceive the imbalance amount as something that mostly lies outside of its control and is part of *the cost of doing business*.

Not only can imbalance costs make up a substantial part of overall marketing costs but hardly foreseeable price peaks constitute extreme financial risks, such as happened during the summer of 2019 in Germany [11]. With an increasing share of renewables in the energy mix, such costs as well as their indirect insurance risk, will also be felt in consumer electricity prices.

The obvious response is to create a more responsive grid infrastructure that is better shaped to fully use the energy produced by renewable energies and also a grid that reacts more efficiently to imbalances. Many different papers have already analysed the benefits of using flexibilities in combination with renewable energy resources. Kirschen, Ma, Silva *et al.* discuss the overall need for flexibly scheduled consumption and generation under various wind generation development scenarios [12]. Schultz, Sellmaier and Reinhart design a concept to regulate demand side power consumption in reaction to renewable energy production [8].

In other studies, the possibilities of flexibilities in a balancing market [13] and estimated future market value of such flexibilities in spot and reserve markets [14] are analysed. Hirth investigates this point more specifically and demonstrates how wind generation works hand in hand with other flexible power generation methods [15]. These approaches share a focus on large scale flexibilities, such as hydropower. In order to open future flexibility markets for small participants, an open system for energy services [OS4ES] with a registry for fast detection and allocation of flexibility offers has been designed in an EU project [16].

Olivella-Rosell, Rullan, Lloret-Gallego *et al.* provide a comprehensive model for battery assets, optimising for overall cost of operation, energy market and balancing market [17]. Other authors have tackled research problems that account for a combination of renewable generation and flexibilities. In [18] a portfolio of a dispatchable power plant, a storage, and an intermittent energy source are optimised on the day-ahead and balancing market. Díaz, Coto and Gómez-Aleixandre look into a similar problem but combine multiple markets such as day-ahead, intra-day and imbalance market into a single equivalent market. Based on this novel approach, an optimal bidding sequence for wind energy and an energy storage option is developed [19]. In these cases, the storage option can be controlled at will with very little constraints on how and when it can be used.

The possibility to use flexibilities specifically to reduce imbalance costs has been addressed to some extent in the literature. Bathurst and Strbac develop an algorithm to plan energy storages amid a wind portfolio, where diverse factors such as price spread, market closure times and expected imbalance penalties are considered [20]. However, in this model arbitrage prices were known in advance and balancing prices known at market closure. Therefore this research cannot answer how uncertainties and forecast errors can be incorporated into a market and scheduling strategy. In [21], freely controllable storage options such as wind and a flywheel are used to mitigate discrepancies between the forecast and the production of wind power.

However, as more and more flexible energy resources enter the energy market, they might not be able to make full use of their flexibility. Physical and technical infrastructure in small resources might not meet the necessary criteria for the balancing markets. Furthermore, the flexibility might be constrained. For example, consumption could only be delayed by some hours inside a predetermined time frame. Such resources might not capitalise on their flexibility at all, because marketing costs would be too high in relation to possible profits.

Currently, the regulatory regime demands from every control group to always strive for a balanced control group - even if a beneficial deviation would be possible. A grid design where such short-notice behaviour is implemented is often called *smart balancing*. [22] describes how the German system could be restructured in this way.

Even if such changes are not implemented, small flexibilities could still provide a balancing service by being integrated to a control group of renewable energies and by trying to reduce forecast deviations. This type of combination could represent an innovative solution in relation to the aforementioned problem of imbalance prices. The flexibility could offer significant value in reducing imbalance costs and thereby increase its overall revenue. In such cases, the flexible energy resource would plan its schedule so as to be able to change its charging power in real time, either by increasing or decreasing it. This power would in turn be used to offset imbalances, effectively acting like a private form of balancing energy.

2.3 Remaining Questions

To conclude, extensive research is carried out to determine the value, use and scheduling of flexibilities. However, these often consider storage options that are controllable without significant time or power constraints outside of their technical configuration. In other cases, more constrained flexibilities, such as home appliances, are analysed but only in their current configuration. The available solutions are often optimised for specific cases or the underlying models are not openly accessible. As such, there are many complex algorithms for optimally scheduling and theoretically planning flexibilities but these do not offer an accessible way to estimate the possible energy cost reduction by introducing flexibilities to a previously inflexible consumer.

Moreover, the economic value of integrating a flexible energy resource for balancing purposes with a second portfolio is a pressing issue. However, doing such a calculation in a universal way is nearly impossible, since many individual factors influence the outcome:

among others the type and forecast accuracy of renewable resources, the size of the portfolio, or the risk aversion of the operator. However, as a first step, the perspective of the portfolio can be excluded to find the marginal costs of the flexibility for constraining its optimisation and offering balancing power in the first place. Such a cost would need to be lower than the benefit for the renewable portfolio in order to increase the overall value of the system through integration.

Based on these findings, this paper sets out to develop a methodology and framework for answering two fields of questions:

1. What are the benefits, in terms of energy costs, of adding flexibility to a currently inflexible energy consumer? Any extensive answer must also touch on detailed questions concerning the configuration, such as: For how long should the storage last? Or, is a certain combination of charging power to delivery obligation especially efficient?
2. When such a flexible consumer offers balancing power it necessarily foregoes price opportunities. How large is the premium in energy prices after constraining the optimisation in this way?

3 Requirements Analysis

Having formulated the central research questions, this chapter defines the methodology for finding suitable answers. With the goal of developing a software simulation, the scope and basic design principles of the underlying code are formulated.

3.1 Research Design

An appropriate way to showcase the potential in cost reductions but also the behaviour of a flexible energy resource is a software model. As a product of this work, different storage configurations and marketing scenarios could be evaluated in how they minimise imbalance costs and which factors play important roles in making each work. However, the goal is not a software infrastructure that could be deployed but a simulation that is able to estimate outcomes sufficiently close to reality. As such, decisions taken in the simulation should not be based on future data, as long as a similar behaviour would be impossible to realise in a real world scenario.

To represent the basic building blocks of a flexible consumer, the software model would need representations of the delivery obligation, a definition of the maximal charging power and the capacity of the energy storage. Further details, such as a gradual loss of energy over time or imperfect energy conversion efficiencies, can be implemented.

Given these physical parameters the software should simulate marketing scenarios, which define how and when trade orders could occur at which prices and, as a result, generate an optimal schedule for minimising costs. In order to sufficiently resemble the complexities of energy trading the energy spot markets need to be modelled: a day-ahead market with a unitary price auction as well as a continuous intra-day market. In these markets, the trading of hourly products, which are the most liquid market, must be fully implemented, while trading on the market for 15- and 30-minute products would increase the fidelity of the simulation. Both day-ahead and intra-day market can be assumed to be large enough so as not to be influenced by the behaviour of the simulation.

Price levels at the spot market and imbalance prices are already closely linked to renewable generation. Therefore, the simulation must be able to simulate various weather situations and their effects on the optimisation goals.

Of course, many different regulatory regimes exist which will necessary change the results of any optimisation. The model should be focused on the current German regulatory framework governing the energy markets.

3.2 Implementation Requirements

The simulation should be easily adaptable to different parameters so these can be set and varied at a later time and without changing the source code. Such parameters should be at least:

- Capacity of the storage
- Maximum charging power
- Delivery obligation
- Any further physical parameters of the flexibility
- Day-ahead market prices
- Intra-day market prices
- The strategy how and when to block the optimisation in order to reserve capacity.

The described software simulation should be implemented in such a way that the behaviour and decisions inside the optimisation are reproducible, comprehensible, and saved for later analysis in an easily readable and interpretable format. From this log, at least the following questions must be answerable:

- What were the optimisation steps?
- How high were the energy costs for the flexibility?

- How was the flexibility used? What was the final schedule of the flexibility and how was it amended over the course of the simulation?

The source code in which the simulation and optimisation is written must be structured and reusable, so that the code could be extended in the future, be transferred to a different language and also be used by a third party as is. Furthermore, different marketing strategies should be implementable using the framework provided by the code. For these reasons the internal logic as well as the interface must be well documented.

4 Methodology and Implementation

Building on the basic framework and requirements of the software, this chapter presents the design and implementation of the finished software library, its assumptions, and design decisions. The functionality and capabilities of the developed software optimisation is demonstrated by walking through the different marketing strategies. An optimisation solely on the day-ahead market reveals how physical limits are respected during the simulation. This concept is extended by re-optimising the schedule continuously on the intra-day market. Lastly, the method for offering balancing power is described. The chapter ends by demonstrating the reliability of the optimisation when scaling and changing input parameters.

4.1 Theory and Design Decisions

The set of possible physical parameters implemented in the model represent the basic building blocks of a flexible consumer: a maximum charging power, a storage capacity, and a delivery obligation, but no other physical parameters can be set. The delivery obligation is also defined as a constant power draw from the storage. While this represents a stark simplification in many cases, a time-dependent delivery obligation can be abstracted to a constant delivery obligation over time with the assumption of some kind of energy storage.

To complete the configuration in the simulation, a null state has to be set, i.e. the amount of energy stored at the beginning and end of the simulation. Throughout the simulations, this value is set at 50 % of the capacity.

The core of the optimisation is implemented in an abstract and strategy-agnostic way. Figure 4.1 depicts the algorithmic logic behind one optimisation cycle. As illustrated, for each point of time in the optimisation the algorithm expects definitive prices which are used to calculate the least-costly schedule. Hence, more complex price forecasts where

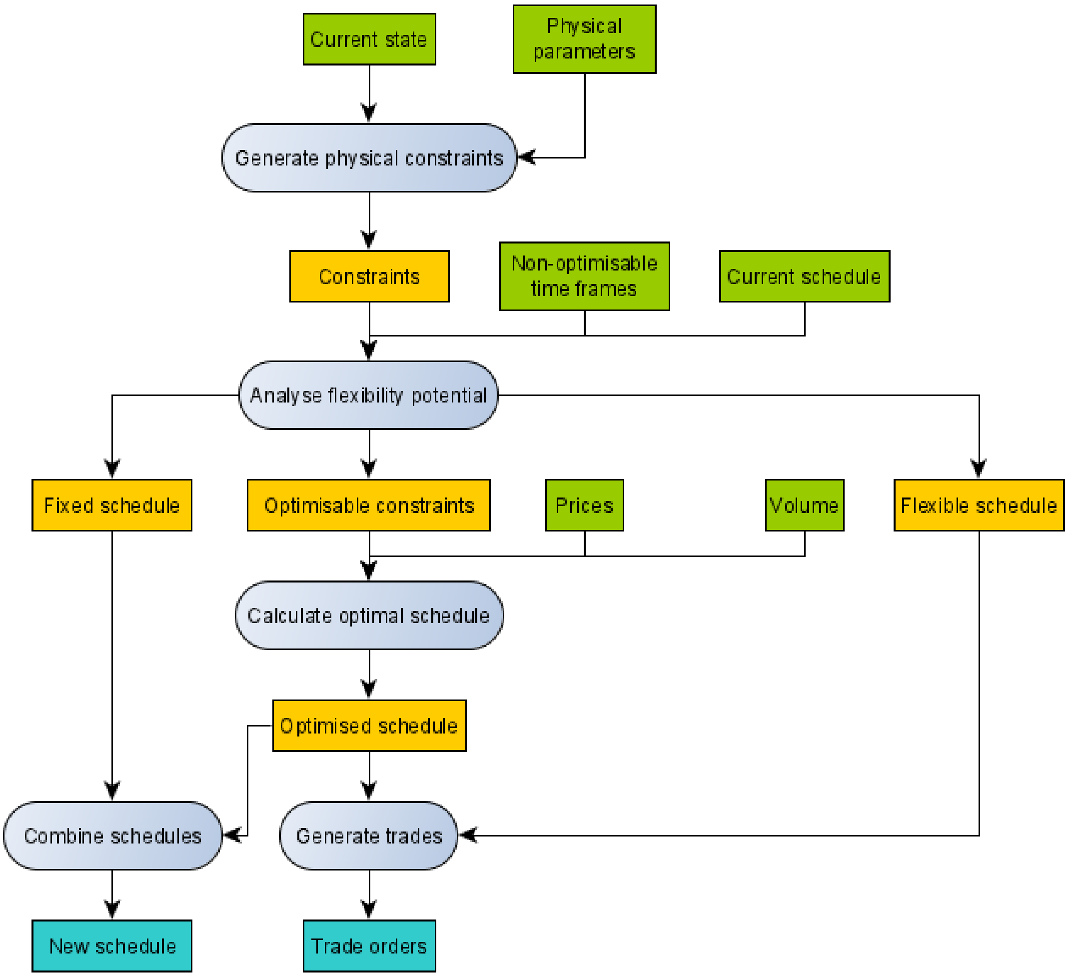

Figure 4.1: Activity diagram for one optimisation cycle (inputs = green, internal values = yellow, outputs = teal).

not only one expected value but also a certainty or a range are provided cannot be used to their full potential.

Each part of this optimisation cycle has been extensively unit tested to verify the correct implementation and assure that internal interfaces work as expected. All in all, the validity of the optimisation algorithm was consolidated with 138 test cases and a test coverage of 100 %.

The optimisation algorithm is based on optimising on discrete integer values. This choice greatly reduced complexity. However, as a consequence, the physical parameters of the system can only be described by integer values. Concerning the charging power, the simulation will assign any integer value between zero and the maximum. How the system can still be scaled variably and simulate configurations with any rational number is demonstrated at the end of the chapter.

As a non-continuous optimiser, the simulation also only handles discrete time intervals. As a design choice, the algorithm only optimises one set of prices per optimisation cycle. An extension to this architecture to allow for example the parallel trading of hourly- and 30-minute products would need to be developed in the future.

The physical constraints of the flexible consumer are not affected by weather conditions. Thus various weather conditions and their relation to optimisation results are simulated by relying on recorded data, for example day-ahead auction prices and imbalance prices as they occurred in Germany. Since the simulation itself is not intrinsically linked to this data, one could supply any sequence of price data to the optimisation.

The developed software library also provides functions which build on the developed optimisation framework and make simulating three specific scenarios very intuitive:

1. *Day-Ahead Optimisation* The day-ahead market is simulated in a 24-hour rhythm. The energy needs are distributed over the hours so that the minimal price is reached and energy constraints are respected.

2. *Intra-Day Optimisation* The process of DA-optimisation is kept as is. However, the intra-day market can be used on top to benefit from price differences. During each hour, the algorithm checks whether a revenue can be generated by selling and buying orders for different delivery time frames on the intra-day market, energy constraints are respected in evaluating possible trades.

3. *Blocking Optimisation* This adaptation of the second strategy adds complexity by buying a set amount of power on the day-ahead market for selected times and blocks these hours from changes in the intra-day optimisation. Thus, the financial consequences of offering balancing power can be simulated.

The following sections show in depth how each of the strategies are implemented and which further design decision in modelling the markets were taken. Whether these strategies and their assumptions correctly model the real world cannot be as easily tested as the internal optimisation. How these strategies could be improved upon is discussed in chapter 6.

In addition, the appendix offers a more detailed look on how these strategies were implemented and how new strategies can be designed while using the existing interface. The source for the code of the complete library is available on a public repository[1], where also a complete manual for all functions can be found. All code for creating the data shown in the following chapters is also published in a public repository[2].

4.2 Day-Ahead Optimisation

The behaviour of the optimisation algorithm will be displayed over three days (1st to 3rd July 2020). This exemplary system has a storage of 20 MWh, a constant delivery obligation of 1MW, and a maximum charging power of 4 MW. Every day is simulated consecutively so that at midnight the charging state will be again at the starting state, which is half of the maximum capacity or in this case 10 MWh.

In a real world scenario, no prices in the day-ahead market could be known in advance. However, it is reasonable to assume that based on weather and subsequent market forecasts, the relative structure of the day-ahead prices can be closely forecasted. For this reason, actual day-ahead auction prices are known in advance in the simulation process.

The simulation is carried out by first building a data frame with charging constraints on the flexibility. To offset the discharge, 24 MWh are spread efficiently over the day and according to the physical limits of the flexibility. By visualising the resulting data (see figure 4.2), the algorithm can show that the physical constraints of the flexibility were respected and that a schedule which minimises costs was picked. This simulated

[1]Repository of library code: https://github.com/henobe/flexoptr
[2]Repository for simulations: https://github.com/henobe/flexoptr_simulations

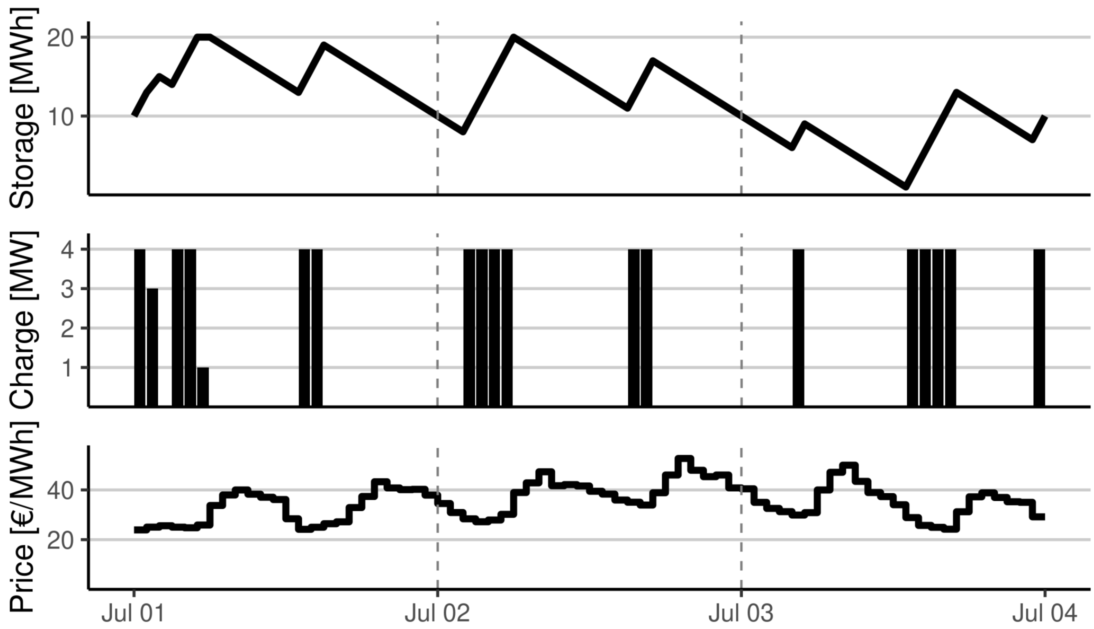

Figure 4.2: Exemplary result of the day-ahead optimisation. Physical limits for storage state and maximum charging are always respected.

configuration was able to lower energy costs by 22.55 %. For comparison, were it possible to charge only once per day (by increasing the charging power and storage capacity) and thus only charge during the cheapest hour of each day, energy costs would have reduced by 29.1 %.

4.3 Intra-Day Optimisation

The previously described approach is now extended to intra-day markets where the objective is to further reduce overall costs. As opposed to day-ahead unitary price auction, prices are not constant nor equal for all market agents. Where the day-ahead auction happens once a day for all hours of the following day, the intra-day market is continuous with a rolling trading window. Therefore, the price and auction mechanism needs to be modelled in a different way.

Theoretically, the complete historical order book could be used as a data basis to replay each trade on the intra-day market. However, such an approach without some kind of speculative logic concerning price developments would not resemble the optimal behaviour for an energy system that is not forced to trade - all energy needs are already covered from the day-ahead optimisation.

The basis for modelling intra-market opportunities as used in the simulations of this paper are index prices. These represent the weighted mean price of all trades for a certain product over a period of time. The *ID1* for example includes all trades that occurred during the hour before the time of delivery.[3] The simulation will thus evaluate index prices for different hour-products, once per hour.

Market prices on the intra-day market are thus represented by two index prices. For the hour after the current one, the ID1 price is assumed. The following two hours after that are approached via the ID3. For example: The simulation would assume it is now 13:00. It would then think it could sell and buy energy for the ID1 price for the hour 14-15. Likewise, it would be able to buy and sell for the ID3 for the hours 15-16 and 16-17.

This approach is certainly difficult to translate directly to a trading strategy outside of a simulation. Prices available at a certain point in time will not reflect any index or average. Being able to consistently trade at index prices is difficult and not a given. Moreover, one could theoretically already start trading earlier and include the ability to trade for the hours of 17-18 or even 20-21. However, realistic market prices for several hours in advance to delivery are difficult to estimate via index prices. This makes the simulation quite conservative in the prices it is able to generate, but ensures that the overall performance of the optimisation is comparable to the behaviour of a trader who represents the market average.

During the hourly and continuous optimisation the algorithm is never speculative and will never sell or buy a position without doing opposite trades of the same volume. Inside these boundaries, it is now the objective of the algorithm to generate a profit by rescheduling its power. The original prices, according to which the day-ahead schedule was designed, are no longer of importance. They should be considered sunk costs.

By analysing the results of the optimisation, this process can become clear. After the day-ahead optimisation, 12 MWh were scheduled from 1 AM until 6 AM on July 1st. After the intra-day optimisation this schedule looks different (see figure 4.3).

[3] Since the market closes half an hour before delivery, the ID1 effectively records the last 30 minutes of trading.

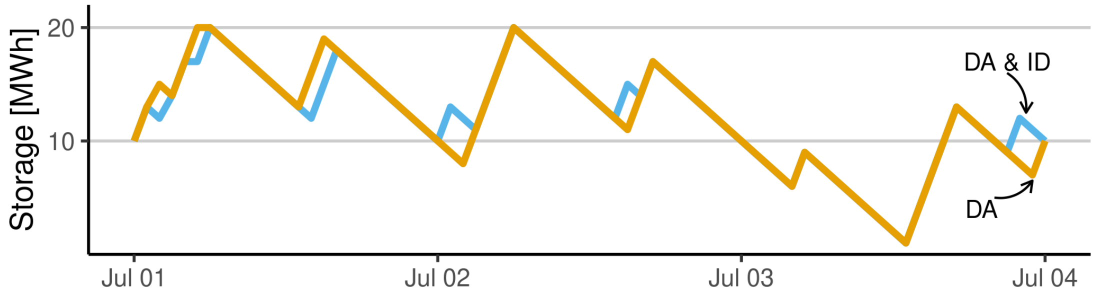

Figure 4.3: Changes induced by optimising the day-ahead schedule with the intra-day logic.

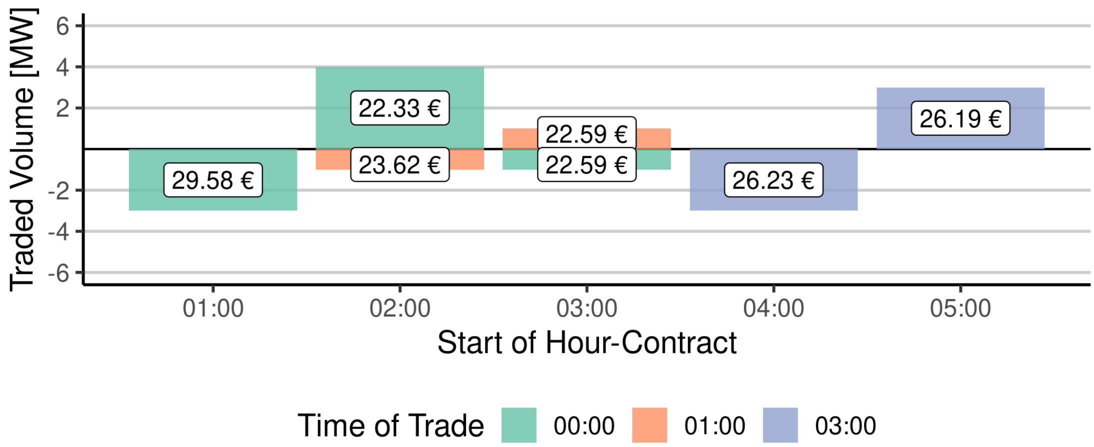

Figure 4.4: Showcasing selected hours of the trade log in the intra-day optimisation.

The trade log (see figure 4.4 for a visualisation) from these hours can explain the exact details:

1. All options for hour 1 (3 MWh) were sold and bought in hour 2. Hour 2 was cheaper than hour 3, so an additional MW was shifted from hour 3 to 2. A further shift was not possible, since the maximum charging power was now already scheduled for hour 2.
2. The price for hour 2 changed and now hour 3 was cheaper, so one MW was shifted back.
3. Even small price differences are used, as shown in hour 4 to 5. This illustrates that the algorithm will perform any trade combination where a net positive revenue is generated. A fee per trade or any other similar trading cost as can exist in actual marketing is not taken into consideration.

Even though the amount of energy was minuscule and the energy prices were relatively similar and stable over these hours, the buy and sell trades generated a profit of € 23.16 and were thereby able to reduce the energy costs of these hours by roughly 7.7 %. Over all three days, the ID optimisation generated a net profit of € 105.76 which means that average energy costs were 25.97 €/MWh. This is roughly equal to the average of the lowest quartile of day-ahead prices (26.04 €/MWh) over all three days.

4.4 Preventing Optimisation

The algorithm can accept times where trades are blocked, which means that a pre-planned schedule is incorporated into the overall optimisation schedule. For the specified times the pre-logged power is not changed. In effect, when the pre-scheduled power is greater zero, the necessary energy is bought on the day-ahead market and kept stable during all optimisation steps.

This functionality has two obvious applications:

- As described in the previous chapters being able two deviate from the schedule will induce an imbalance, which could be used to balance the deviation of a second system.

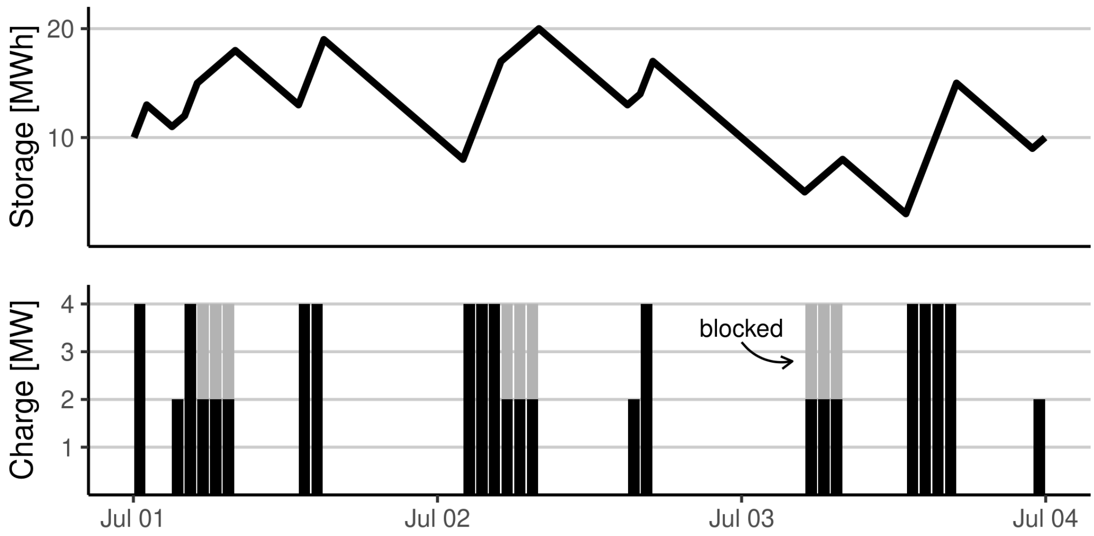

Figure 4.5: Optimised schedule while binding some hours to a fixed power.

- On top of raw energy prices, the operation of an electric consumer also needs to take into account further costs. One of such costs is a grid charge that is typically calculated based on the how much power was drawn during certain times from the grid. Hence, by blocking any charging during some times, such charges can be reduced.

The first application is explored in more detail in this paper. By setting up some hours at half of the installed power it would be possible to provide a positive and a negative deviation equally. Furthermore, it could be assumed that the imbalance of any portfolio that is to be matched, fluctuates around zero and will over time equate zero. This allows the simulation to optimise the rest of the schedule around these constricted times.

Compared to reality, these assumptions are certainly a simplification. When the sum of the artificial deviations does not equal zero, rebalancing the schedule would be possible via short-term buy or sell orders on the intra-day market on top of the optimised schedule.

By applying this logic to the previous example, we can see the amended schedule and accompanied states. In this scenario, the power is kept at half maximum each day from 6 to 9 AM (figure 4.5).

This comes of course with an added cost. On the one hand, the six MW from 6-9 are bought on the day-ahead market, regardless of the price. On the other hand, by having these 6 MWh already planned, this constricts the flexibility for the remaining hours. In this case, this modification already had a strong impact on costs. It increased costs by € 135, which would translate into a relative price increase in marketing costs of 7 %.

4.5 Scale of Parameters

The previous examples were all based on a specific configuration with clearly defined physical parameters. However, when analysing the differences between various sizes of applications, one can generalise the output of the simulation by making the results relative to some baseline. For example, in figure 4.6 the configuration of the previous examples has been scaled by three and ten.

All costs simply increase by three and ten respectively while the relative difference between simulations remains constant - this is based on the assumption that the actions of the algorithm are too small to meaningfully affect the market behaviour. This property has two helpful properties:

1. By simulating and comparing a set of parameters the results can be extended a physical system of any scale.

2. It becomes possible to simulate configurations where the parameters do not have *whole-number* values. For example, a system with a delivery obligation of 1.3 MW, a maximum charge of 2.4 MW and a storage capacity of 3.5 MWh could not be directly simulated with these inputs. However, by multiplying these values by 10 and then again dividing the simulation results by ten, the correct values are calculated.

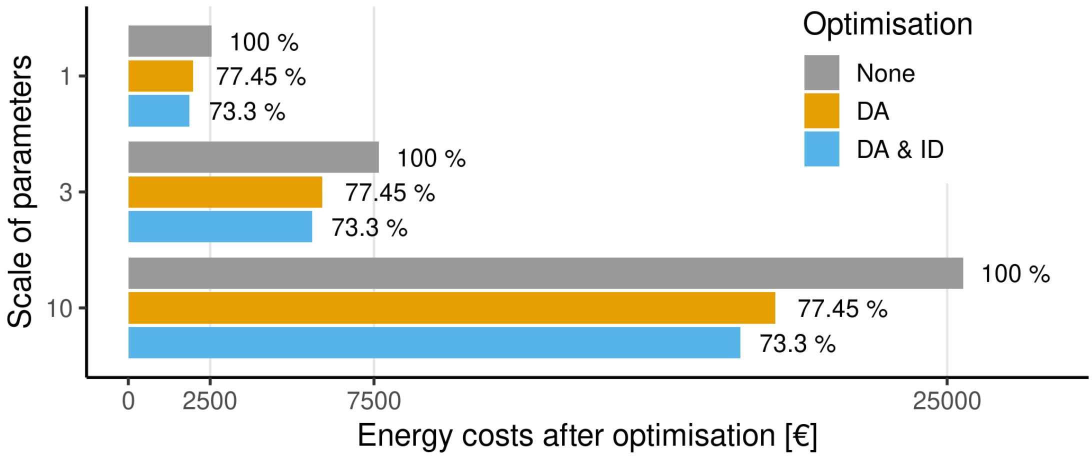

Figure 4.6: Changing parameter scales does not change the performance of a simulation.

5 Simulation Results

The functionality and inner logic of the optimisation algorithm has been demonstrated. This chapter will begin to formulate answers to the original research questions. By comparing the results of hundreds of simulations, the effects of changing the physical parameters become visible. A different analysis estimates the effects of trading *better than average* at the intra-day market. Finally, simulations incorporate a theoretical balancing energy service and link its cost to the general price structure of the blocked times. The analysis presented here is by no means exhaustive, but a first step in showing which areas are particularly interesting and surprising and which demand further investigation.

5.1 Relation of Charging Power and Storage Capacity on Marketing Costs

Having seen how the simulation optimises a schedule for the day-ahead and intra-day process, it is most interesting to compare the results of simulations with varying parameters. As previously described, three key parameters will describe the physical constraints of flexibilities: A constant power demand on the storage, an adjustable power input for the storage and the capacity of the storage itself.

5.1.1 Configuration

Being able to adjust three parameters, each simulation has two degrees of freedom in this regard. For simplicity the delivery obligation is described by the variable L [W]. The capacity C could have any size, but it is most interesting to look at the range of one hour (or $C = 1h * L$ [Wh]), i.e. a full storage could supply the energy for one hour without further energy input, up to twenty-four hours, that is $C = 24h * L$ [Wh]. This upper limit is connected to the logic of the simulation and structure of the market process: Only the next 24 hours are traded on the day-ahead market.

The range of values the power input I can take is also logically limited. The system should be able to charge the storage, therefore $I > L$ must always apply. In the following simulations the typical minimum input power was $1.05 * L$. Furthermore, being able to fully charge the storage from an empty state describes the maximum reasonable power. Since the simulation works in blocks of one-hour energy products, any faster charging rate than $I \leq \frac{C}{1h} + L$ would not yield any benefit.

This allows to cancel out the exact size of the three parameters since the results stay the same as long as the relation between these three variables is kept. For simplification, capacity and input can therefore be described as general properties of any flexibilities:

- C is the length of time the storage could possibly fulfil the energy needs. Henceforth simply referred to as capacity.
- I is the input or charging parameter, described either via the ratio of maximum charging power to constant delivery obligation or as the percentage of how much of the storage could possibly be charged over the course of one hour, considering a constant discharge of L.

5.1.2 Results

A two week period during the summer of 2019 (1.-14. July) was selected as the time frame for simulation data. Over this period, capacities ranging from one to 24 hours of possible storage were optimised. For each capacity, a wide range of possible charging power configurations was simulated to demonstrate the influence of each parameter.

By focusing on the marketing cost in relation to a baseline of *no storage*, the results will be comparable even between different scales of storage. This baseline will be used throughout the following analysis and will be calculated by multiplying the energy need per hour, as defined by L, with the energy price on the day-ahead market for each hour of the simulated time span. The term cost reduction is used to describe the difference between the baseline costs and the relevant optimisation (only DA or DA & ID).

According to the simulation, a configuration with a storage that can last a full day and be charged very fast is able to halve energy costs (slightly below 45 % for simple DA

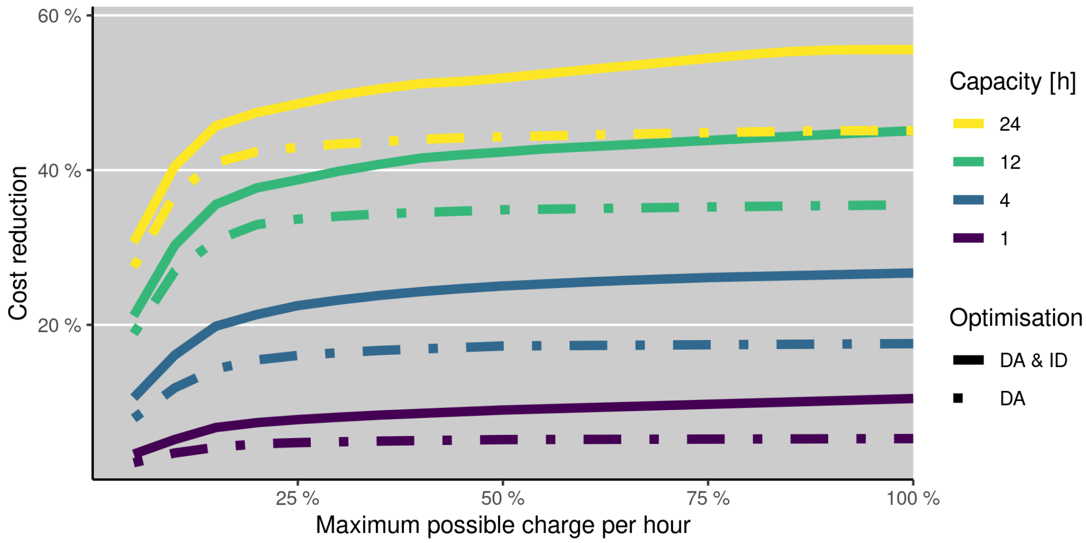

Figure 5.1: Simulation results for energy cost savings, only selected capacities visualised.

optimisation). This is near the theoretical day-ahead optimum of 48 % cost reduction, which could be achieved by charging only once per day exactly at the time with the lowest prices. By utilising the intra-day market on top the optimisation was able to realise cost reductions of up to 60 %. Even a storage unit that can only sustain the energy needs for four hours and has a moderately sized charging module can reduce energy costs by roughly twenty to thirty percent. At the same time, even though the simulation demonstrates improvements with rising power, there are clear diminishing returns to adding more power to the system. For better overview, a selection of possible capacities is visualised (fig. 5.1).

As defined in the algorithm, the amendment of the schedule on the intra-day market will always yield better results than simple day-ahead optimisation. Nevertheless, for a capacity that lasts 4 hours and an I that can charge about a quarter of the storage over the course of an hour, the difference between day-ahead and intra-day optimisation stays stable with roughly 10 percentage points.

In other words, the relative advantage gained by trading on the intra-day market is greater the smaller the capacity. By working with a small capacity the simulation has less freedom in optimising between different times of day and will spread more volume over the course of the day. As a consequence, the intra-day optimisation has more

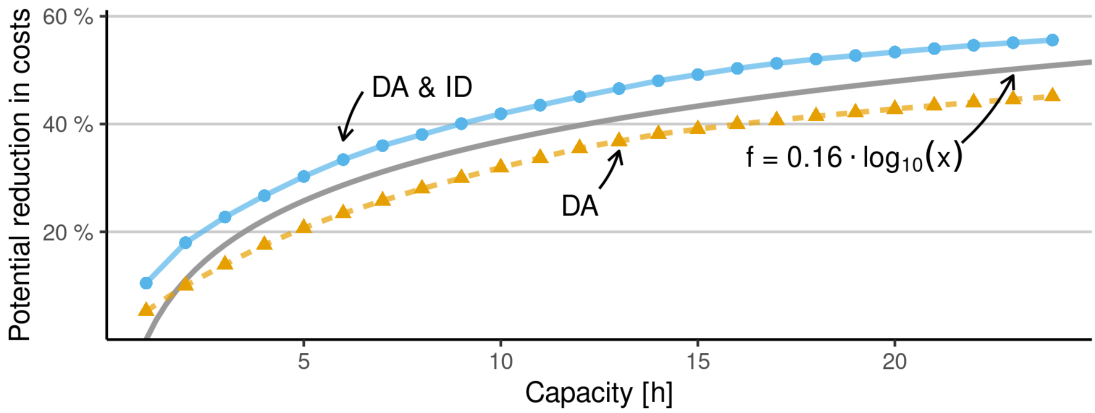

Figure 5.2: Maximum possible cost reduction as function of capacity.

chances to capitalise on price differences between hours. This explains why the intra-day optimisation is much more impactful for configurations with small capacities.

To investigate the relation between capacity and cost reductions more closely, figure 5.2 visualises the maximum possible cost reduction (at $I = C/h + L$) for different capacities. The benefits of increasing the storage size do not scale linearly but logarithmically. For capacities of 4 or more hours the possible savings could be described by the function $f(x) = 0.16 * log_{10}(x)$.

By increasing the capacity the algorithm can better evade hours of high prices during the day-ahead optimisation. Nonetheless, increasing the capacity from five to ten hours will lead to a greater price reduction both in absolute and in relative terms than increasing it from 15 to 20 hours.

Only looking at the potential savings by a large charging method does not paint the full picture. Figure 5.3 therefore illustrates how of much of the reduction potential is realised by smaller charging potentials.

Even at the smallest simulated charging power ($I = 1.05 * L$) around half of the maximum cost reduction for that specific capacity is already reached. Nearly all configuration even reach levels of above 80 % when being able to fully charge over 5 hours. This can be explained the structure of the day-ahead market. Single-hour price peaks on the day-ahead market are rare and thus being able to only charge over 5 hours, as in contrast to say 2 hours, seems to effect the overall optimisation result only minimally.

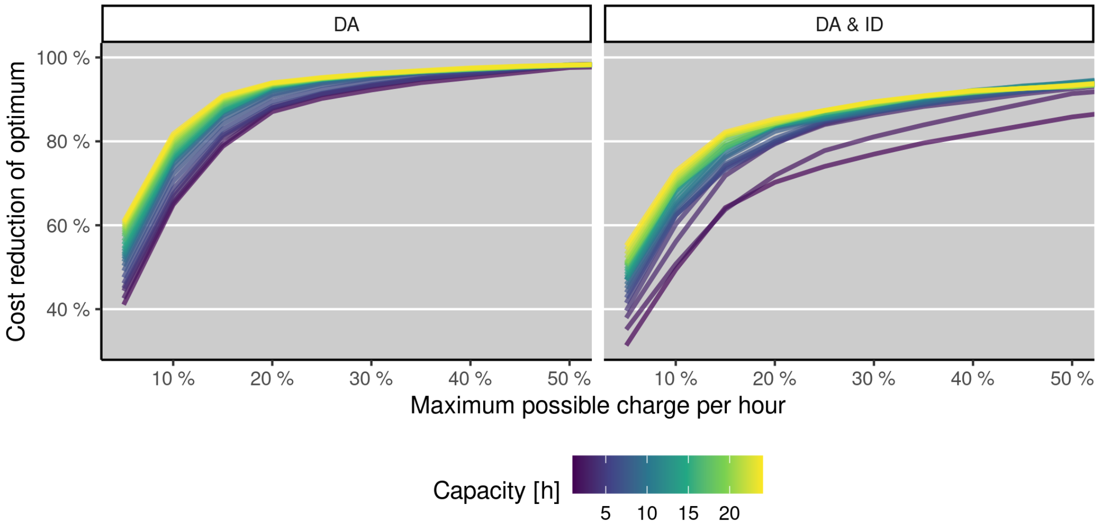

Figure 5.3: Influence of charging power on day-ahead and intra-day marketing.

The difference between different capacities is larger when the intra-day market is used, but this variability quickly shrinks when increasing the charging power. In general, increasing the charging power should be a bigger priority when intra-day optimisation is used. The plots demonstrates that this allows more freedom to react to short time price differences and developments.

5.2 Sensitivity to Price Improvements

The intra-day optimisation as described in the previous chapter in based on evaluating and trading index prices. By design, any intra-day trades are voluntary and always beneficial. That is why it is reasonable to assume that a trader, who could set individual limit prices for buy and sell orders, could be able to outperform an index which is based on the average of all trades, especially when a balanced schedule was already prepared on the day-ahead market.

As noted previously, simulating index prices is a conservative simplification. The effect of improving prices can be modelled in two ways:

1. A trader could be able to secure trades that are x Euros better than the index. Instead of selling for € 20, one could sell for € 22 or instead of buying for € 10 on

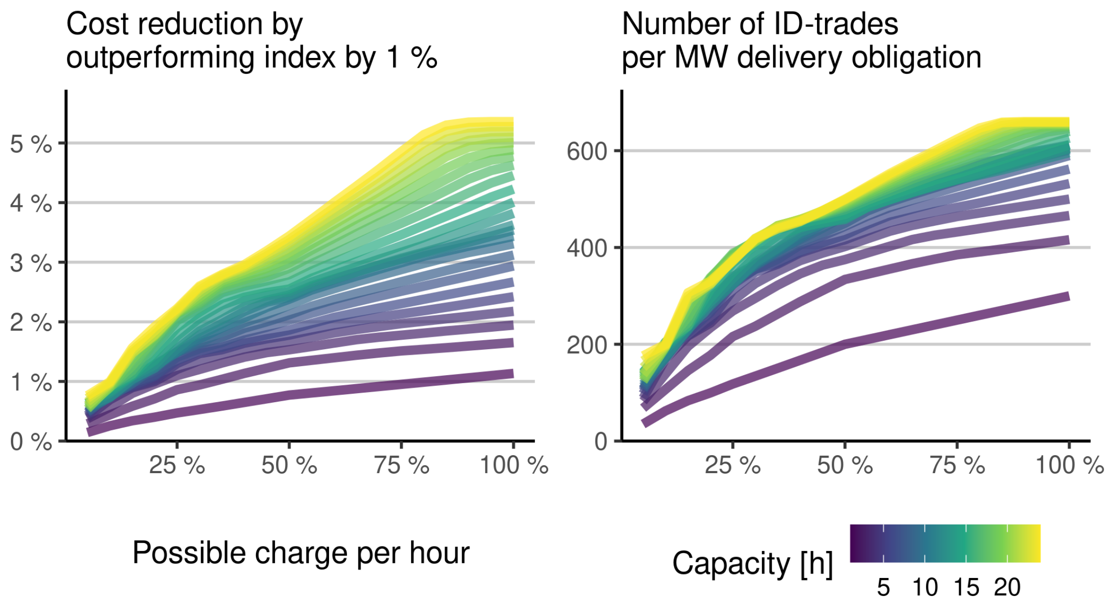

Figure 5.4: Sensitivity to improving market prices for various configurations.

would buy for € 8. This approach would imply that the intra-day price volatility is not connected to the price level. Unfortunately, changing the prices of simulated trades ex post would not reflect the full potential since new trades at the margin would be possible.

2. A second approach is not to improve the trades by an absolute but a relative margin. This incorporates also the opposing assumption: the further away prices are from 0, the more volatile they will be.

Both approaches are visualised in figure 5.4. In this case, the left plot illustrates the effect of improving buy and sell prices by 1 %. (If one wanted to assume a different rate of improvement, the y-Axis could be scaled linearly.) The right plot simply plots the number of trades per simulation and per MW of obligation. This figure should only be used for comparative analysis as the number of trades is linearly connected to the size of L.

Even though both plots share the same basic structure and relationship between their variables, the relative cost reduction as a function of capacity is much more spread out when using the relative approach. Low capacity configurations benefit more, if the assumption that volatility is not dependent on price levels holds true. On the other

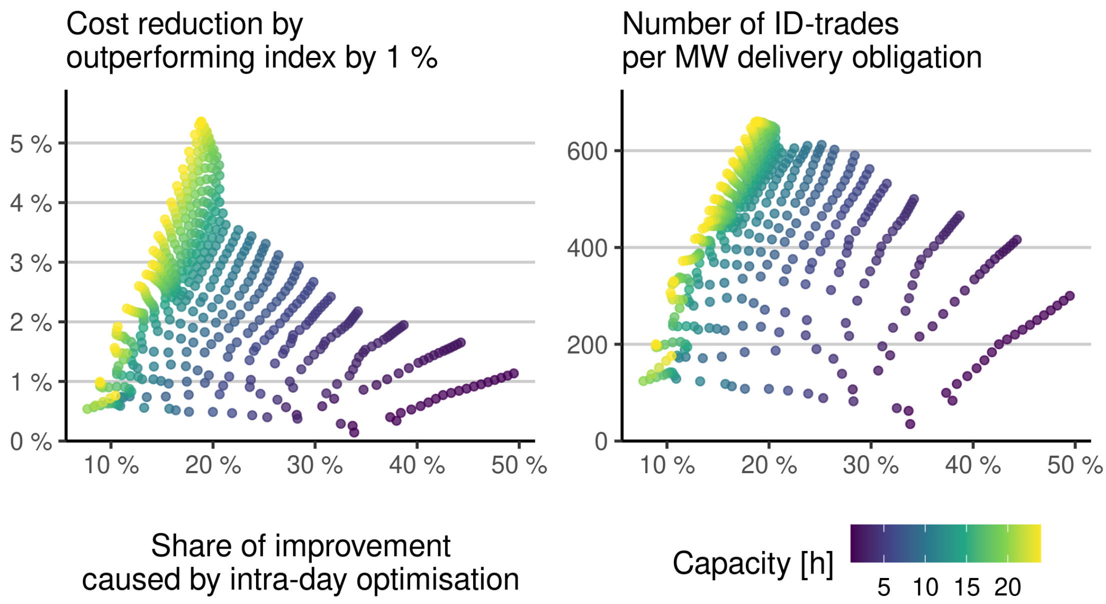

Figure 5.5: Correlation of price sensitivity and share of intra-day profits

hand, believing in the assumption that volatility is indeed price dependent, increasing the capacity shows greater benefits.

Both plots also share a flattening curve on the top right, i.e. for high capacity and high charging power configurations. For those configurations increasing the charging power above 80 % does no longer have meaningful effects on the most efficient schedule.

Extending this idea, one could assume, that the increased benefit of greater capacity and charging power is directly related to the share of overall cost reduction that is due to the intra-day optimisation. Figure 5.5 tests this hypothesis and suggests that there is in fact no correlation. Just being able to generate good profits on the intra-day market does not translate into an equally increased bonus when prices are adjusted.

5.3 Effect of Offering Imbalance Power

The previous chapters have explored the intricacies of minimising energy costs for flexible consumers. However, the ability to flexibly change the power drawn from the grid could represent additional value. The flexibility could position itself as a provider for balancing energy in its own balancing group by deviating from its specific pre-planned schedule.

Such a management would require the evaluation of various marginal cost curves. This chapter will therefore begin to explore this use case by estimating the costs incurred by the flexibility when it makes itself available for such a management, i.e. the price just for offering the service of balancing.

5.3.1 Configuration

The simulation can estimate the price of offering flexibility by planning a certain schedule for a specific hour and then block further optimisation of this hour during the intra-day process.

Evaluating all different scenarios for blocking different hours of a day and their price effect would surpass the scope of this paper (there are more than 16 Million theoretical combinations just in a single day). Therefore, a specific case is evaluated where three different, distinct blocks are reserved.

Imbalance providers are determined by a tender for consecutive four-hour blocks. The resulting imbalance prices, also dependent on the overall grid imbalance, is only known after the fact. However, a merit-order list describing the marginal imbalance price is known in advance. Based on this merit-order list one could calculate a risk metric for imbalance prices each of the 4-hour-blocks and use this metric to determine the time frames of possible balancing by the flexibility.

The simulation is now parametrised to not only optimise a two-week time frame but also block a 4-hour block each day for potential balancing. To increase the general applicability of the results, not only one but three different weeks were chosen for analysis. They each had to comply with a set of criteria:

- There could be no change from or to daylight-saving time to keep the amount of hours consistent.
- Bank holidays should be avoided, since prices at these times tend to be non-representative.
- The three time spans should each be during different times of the year which has an effect on the price structure.

- Times of national or large-scale lockdowns connected to the efforts to curb COVID-19 should be avoided. Energy prices during these times presented a unique structure.
- In each time frame, there should be a single block of four-hour prices with a distinctly higher level of imbalance prices.

Market prices for 2020 were evaluated which lead to the selection of these three time frame:

1. 06.01.2020 to 19.01.2020, blocking the hours 4-8 AM.
2. 01.07.2020 to 14.07.2020, blocking 4-8 PM.
3. 14.09.2020 to 28.09.2020, blocking 12-4 PM.

A more detailed look at the different imbalance prices is presented in the appendix.

At this point an important assumption is introduced. The sum of the imbalance, i.e. the sum of deviations from the original schedule, will over the four hours equal zero. This allows the simulation to optimise the rest of the schedule. It is also a reasonable assumption since a managed portfolio that tends to not have a net imbalance of zero should always adjust its forecast algorithm.

With this assumption in mind, it is also a good starting point to block half of the maximum possible hour for the affected hours. This way, it is possible to react to positive and negative imbalances equally. This setup introduces some further constraints on the possible configurations:

- The capacity must be able to handle two hours on half power, which gives the natural limit of $C > 4h * L - 2h * \frac{I}{2}$ In the worst case, it should handle 2 hours of no input. For a bit of a buffer, 3 hours is chosen.
- Charging at half power for four hours must not exceed the storage capacity $2h * \frac{I}{2} < C + 4h * L$ which leads to $I < C/h + 2 * L$. To retain some flexibility in optimising the schedule, the maximum charging power is chosen at $I \leq 3 * L$.
- Limiting the charging power for four hours at half power must still allow the storage to not be depleted over time, this leads to $20 * I + 4 * 0.5 * I > 24 * L$ which equals $I > 1.\overline{09} * L$. But this leaves no flexibility. Therefore the charging power is set at $I \geq 1.5 * L$ which allows for some optimisation to take place.

In contrast to the previous simulations a specific physical configuration is analysed and visualised. This greatly improves the interpretability of the results. However, the results are still generalisable to other configurations by transforming the physical sizes with their respective ratios. The system chosen has a constant delivery obligation of $L = 2$ MW.

5.3.2 Results

By comparing the relative increase in costs in each simulation (see fig. 5.6), the differences between the different weeks is very apparent. In addition, the appendix includes two further visualisations showcasing the absolute increase in prices. All in all, the increase in costs can be described as moderate. The most flexible configuration incur additional costs of around two to twelve per cent. This range between the different weeks is much smaller for less flexible configurations.

Controlling for the amount of possible balancing power (half of the maximum installed charging power) offers a detailed look at the influence of the different parameters on costs (see figure 5.7). Less flexible consumers have a less pronounced cost increase, but also offer less power for balancing. Increasing capacity and charging power can make offering balancing power relatively cheaper, while it can also do the opposite when the time of the blocked hours is changed. These results hint at complex relations between the different simulation parameters that demand further investigation.

The stark contrast between the weeks can be explained by the underlying price structure and the prices that were necessarily taken as a result of positioning the schedule at half power. Figure 5.8 illustrates the median day-ahead prices of each hour for the simulated two weeks. The first obvious deduction is that each week had a generally different price level. While the simulation for January was forced to buy during the most expensive time of the day, the September simulation was able to make use of prices likely to be included in an unconstrained optimisation. However, buying *only* at half power during these hours has a negative effect on configurations with smaller charging powers.

Therefore, a rather self-evident, result of the analysis can be stated: Systems with greater flexibility (high charging power, large capacity) incur greater financial costs when the blocked hours are times of high prices. The different price premiums not only depend on the configuration but are not even generalisable since they are deeply connected to each day's price structure.

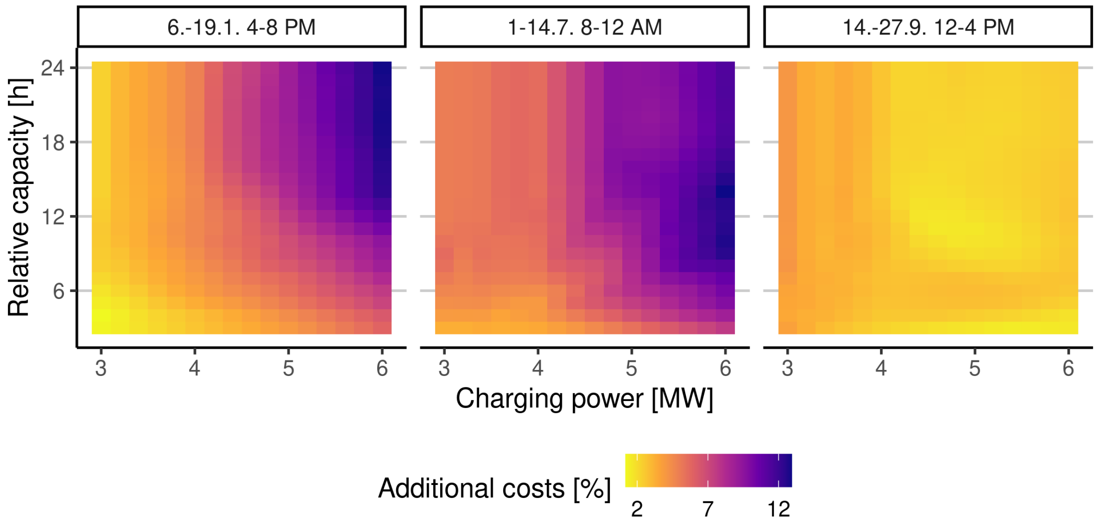

Figure 5.6: Relative additional costs after blocking some hours from optimisation.

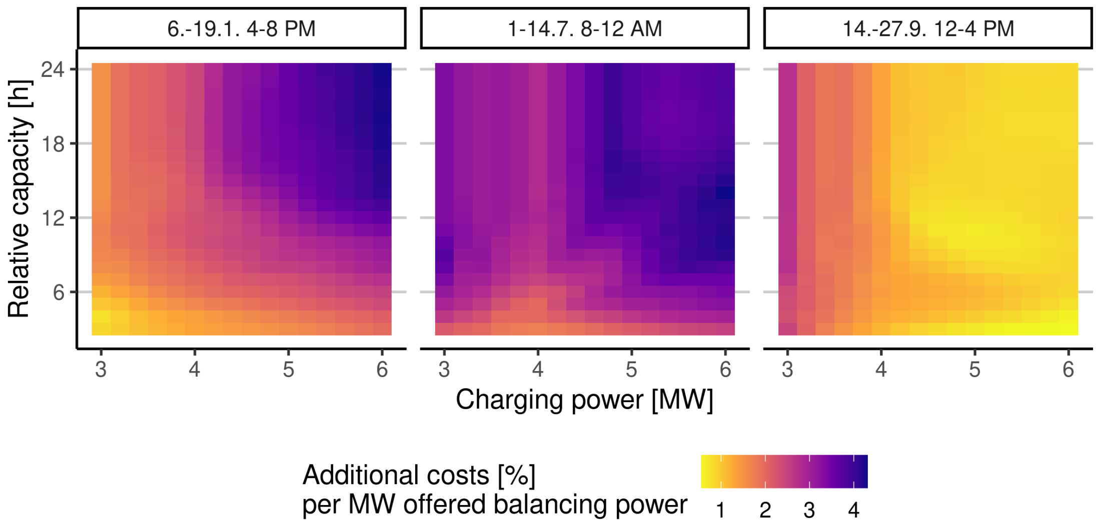

Figure 5.7: Additional relative costs per offered power.

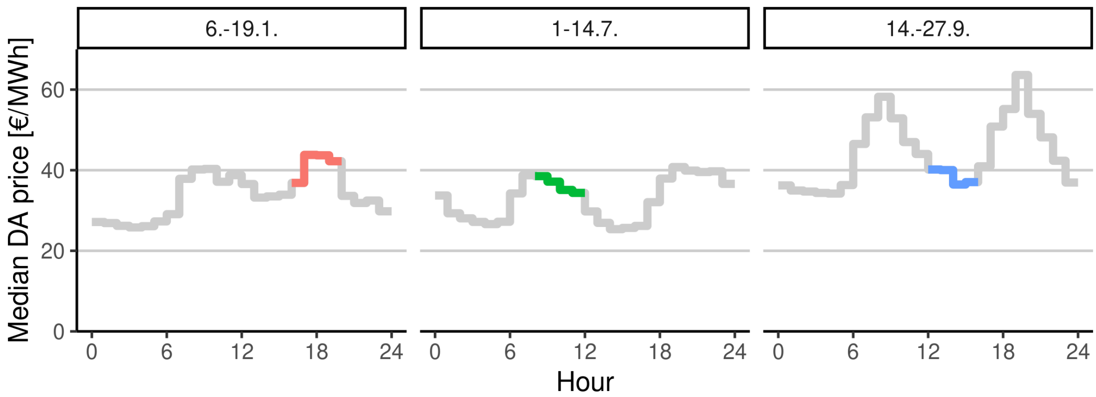

Figure 5.8: Median day-ahead prices in selected time windows, the coloured parts indicate the times when balancing power was offered in the simulations.

6 Discussion

The simulation and optimisation algorithm as presented in this paper incorporates the essential requirements to make its results transferable to a real world context. Essential questions can be answered and addressed in new ways. Nevertheless, there are some aspects which would increase the fidelity of the simulation, but at the cost of increased complexity and adaptability.

6.1 Extensions to the Simulation

The underlying data used in the simulation must be unambiguous for each point in time. However, more complex simulations are able to factor risk assessments and uncertainty into the algorithm, e.g. [17] and [18]. As a first step, the algorithm could differentiate between price forecasts, on which the optimisation would be carried out, and a different price list, which would represent the actually traded prices. The current approach has the clear benefit that a deterministic model produces results where every step is always repeatable and reproducible without deep knowledge of internal states of the optimisation.

Currently, two specific use cases for optimising the intra-day and day-ahead market are implemented and compared. These are of course not the only ways to optimise a resource on the spot market. For example, one might not want to already schedule the energy needs of a whole day on the day-ahead market but only for example 50 % of the daily volume. Subsequently, the intra-day market could be used when the order book is favourable. This new approach would certainly have the potential to further reduce overall energy costs while new factors such as risk assessment and market forecasts would need to be taken into account.

Based on the analysis of the previous chapter, any decision to prepare balancing services should not only take a risk-analysis into account but also the expected price structure.

Currently, the software library does not make an attempt to optimise when and how many hours should be blocked for offering balancing energy. This is not possible as long as the second half, the value for the taker of balancing energy is known. However, the developed software framework could be used as a starting point to develop such optimisations.

All in all, the simulation only looks at raw energy costs and leaves out many other crucial factors which impact the operating cost of an energy resource. The charging equipment might operate at different efficiencies depending of the state of the storage. Among other things, abruptly increasing and decreasing the charging power might lead to a higher wear on physical components and introduce new costs. Such considerations would need to be evaluated before any physical system is built or managed.

6.2 Extensions to the Analysis

The analyses, as presented in the previous chapter, showcase the potential of the developed software optimisation. Nevertheless, some adaptations could be made that only change input parameters to the simulations. A factor that remains unexplored at this stage is value of the starting state. The day-ahead optimisation is programmed to run once a day and calculate a schedule that returns to this state after 24 hours.

Very low starting states would allow for more charging in the morning, while very high states would allow the schedule to be shifted to the evening hours. This will inevitably effect the marketing result of any simulation and will even have a stronger effect when some hours are blocked from optimisation.

A different scenario would be to plan two or three days in advance on the day-ahead market, while only actually trading the next day and repeating the process every day. As a consequence, the optimisation would not return to the starting state of the capacity every 24-hours but be able to flexibly capitalise on low prices in morning or night hours.

The monetary effect of offering balancing services was shown to be most influenced by the decision when to offer this service. Thus, an analysis that more flexibly fits the blocked time frames for each day would provide further insights. As a result of that analysis, one could more realistically compare the eventual imbalance prices to the cost of offering balancing energy via the flexibility.

7 Conclusion

Extensive research is carried out in the field of planning and optimising flexible energy resources. The research proposed here does not offer a competing model. Instead, a specialised solution is presented to model constrained energy consumers and estimate the benefits of using energy markets to decrease energy costs. The benefits of the underlying open-source software library are its adaptability and ease-of-use. The underlying concepts and assumptions are clear and present therefore a coherent programming interface. The software library is therefore a good tool for building complex simulations.

By using this optimisation algorithm an analysis of a diverse set of flexibility configurations was carried out. Energy cost reductions were remarkable. It was demonstrated that even systems with small storage capacities can decrease energy costs by 10 % or more when making use of price differences in day-ahead and intra-day markets. Savings of more than 50 % are certainly feasible for very flexible configurations. When designing flexibilities, both charging power and capacity should be scaled as both demonstrate diminishing returns.

Simulating the benefits of an continuous intra-day optimisation is more complex than only concentrating on the day-ahead market. Therefore, the analysis makes conservative assumptions. In this scenario, making use of the intra-day market for arbitrage trades reduces energy costs in many system configurations by roughly 10%.

Using flexible consumers as private providers to balance forecast errors in a shared control group is a concept that is not yet in widespread commercial use. Since the coordination between renewable generation and the constraints of such flexibilities is complex, this research is only a first step in examining this topic. The analysis comes to the conclusion that offering such balancing energy could be feasible and does not seem to increase costs prohibitively. However, the degree of additional costs is heavily dependent on the system configuration and times when flexibility should be offered.

While fluctuating weather situations present the most promising results, constraining the price optimisation of the flexibility could also be more expensive than paying standard imbalance prices. More research is needed to determine the competitiveness in an operational scenario. Still, such integrated control groups could be a further building block in reducing the risks connected to marketing renewable energy portfolios and decrease the need for grid-wide balancing services.

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A Further Plots and Simulation Results

The link between the logarithmic scaling of simulation results as a function of capacity has already been shown. The figures A.1 and A.2 extend this approach by visualising the same data as 5.1 and 5.4, but having divided each y-axis value by the natural logarithm of the respective capacity in hours.

The overall cost of the simulations in chapter 5 after blocking some hours is described in figure A.3. Figure A.4 visualises the concrete premium per hour and MW of offered balancing power.

Figure A.5 illustrates the distribution of imbalance prices in the selected weeks.

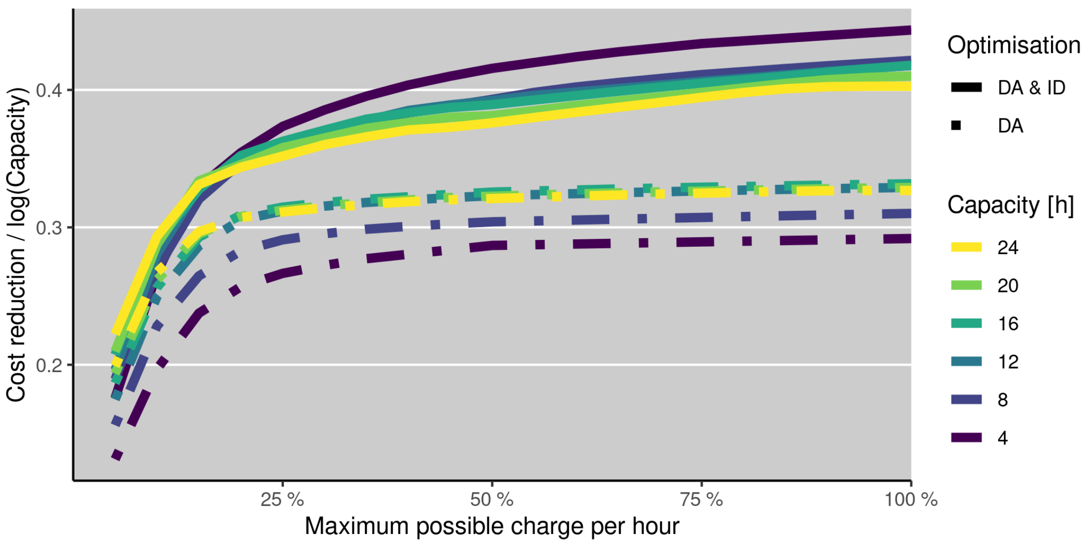

Figure A.1: Simulation results for energy cost savings, scaled to logarithm of capacity.

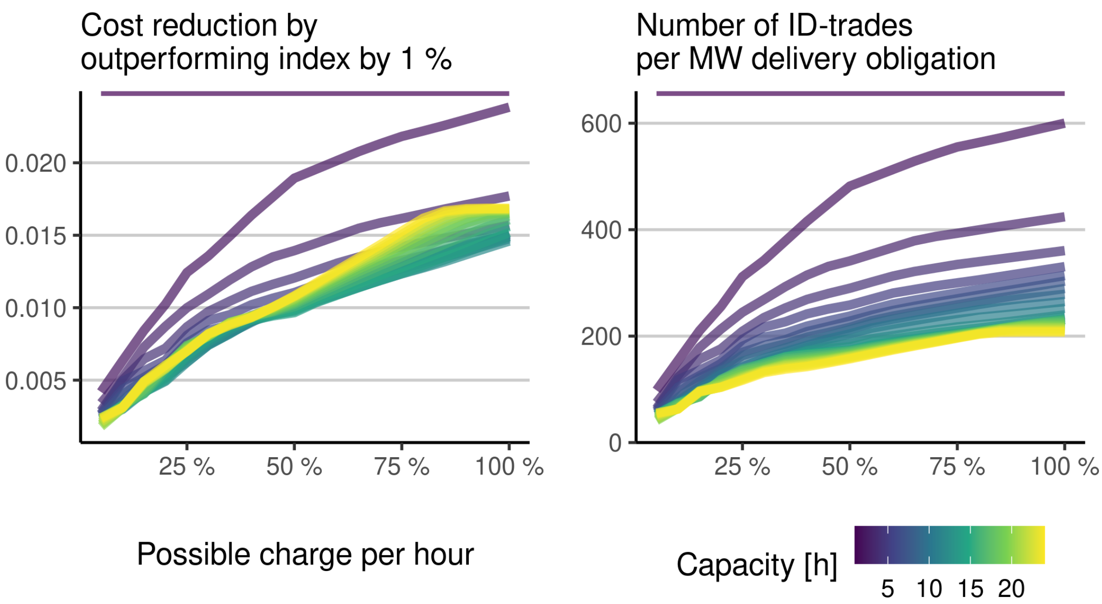

Figure A.2: Sensitivity to improving market prices, scaled to logarithm of capacity.

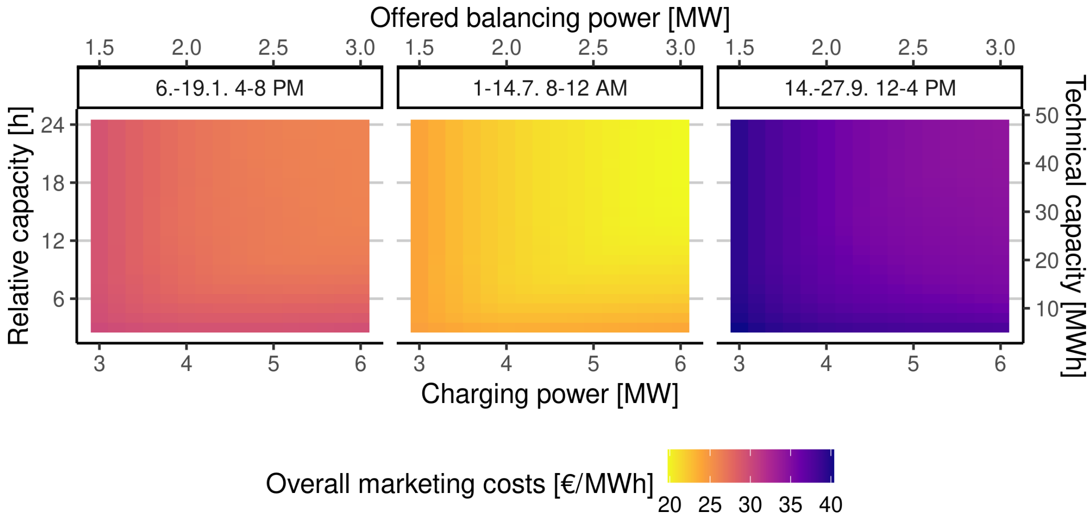

Figure A.3: Overall marketing costs after preparing for balancing services.

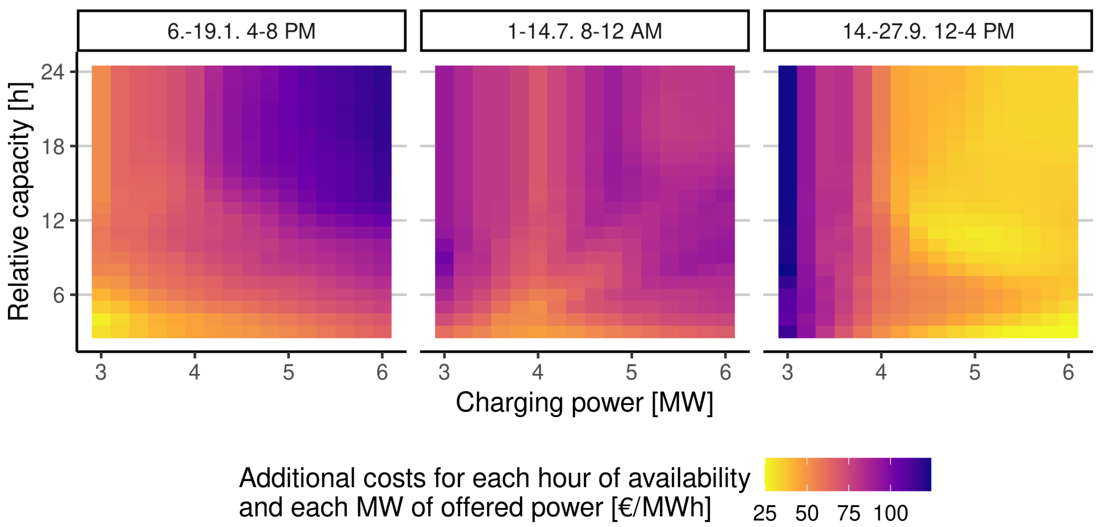

Figure A.4: Additional costs per hour and power allow comparisons to standard imbalance prices.

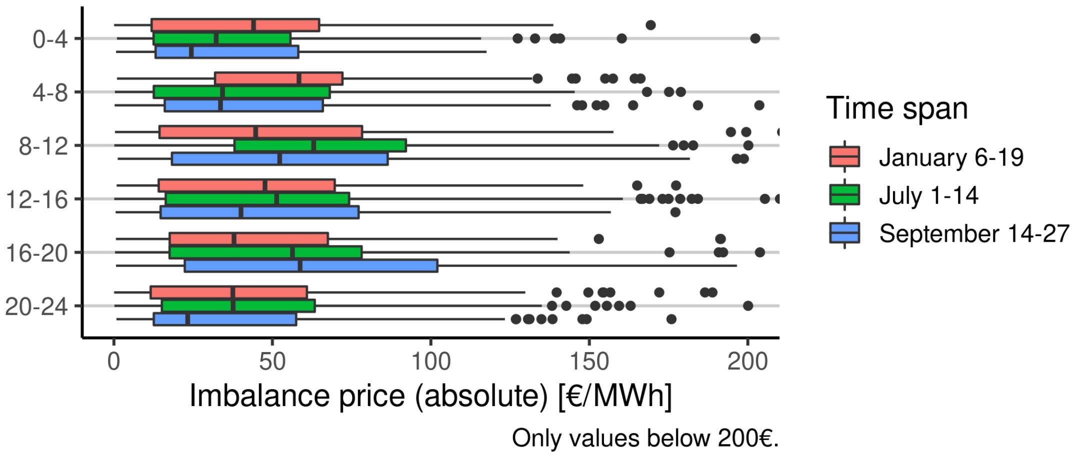

Figure A.5: Imbalance prices for each simulated week.

B Working with flexoptr

The goal of flexoptr is to provide a suite of functions to generalise and ease the modelling of energy flexibilities. By defining base parameters, the needs of a constrained flexibility are calculated, and optimised over price data. Several functions to facilitate the optimisation of more complex market and configuration analyses are also provided.

The only required external package to run this package is magrittr which introduces the pipe operator and is only used for making code more readable. The r-Project has already announced plans to make a pipe operator a native part of base R, development is currently under way. Therefore, a future adaptation of the code which completely avoids secondary packages is possible.

B.1 Installation

You can install flexoptr from GitHub with:

```
# install.packages("devtools")
devtools::install_github("henobe/flexoptr")
```

There are currently no plans to release the package on CRAN.

B.2 Example

Given a flexibility of with the physical parameters of a delivery obligation (constant), a maximum charging power (variable), and a storage capacity an optimal schedule for minimising energy costs can be calculated.

```
library(flexoptr)

base_parameters <- c(
  "starting_state" = 5,
  "capacity" = 10,
  "charge_rate" = 4,
  "loss_rate" = 1
)

sample_constraints <- build_constraints(
  cycles = 10,
  state = 5,
  parameters = base_parameters
)

sample_prices <- c(37, 17, 4, 4, 9, 21, 22, 47, 48, 5)

optimise_constraints(sample_constraints, sample_prices, 15)
#>  [1] 0 0 4 4 2 1 0 0 0 4
```

This approach is extended in the library and many functions are provided that facilitate the analysis of many scenarios.

```
sample_prices_day <- sample.int(50, 24, replace = TRUE)

optimise_schedule(
  schedule = rep(0, 24),
  parameters = base_parameters,
  prices = format_da_prices(sample_prices_day),
  shift = 24 * base_parameters["loss_rate"]
)
#> $schedule
#>  [1] 4 0 1 4 1 0 0 0 4 0 0 0 0 0 0 0 2 4 0 0 0 0 4 0
#>
#> $state
#>  [1] 8 7 7 10 10 9 8 7 10 9 8 7 6 5 4 3 4 7 6 5 4 3 6 5
#>
#> $trades
#>   time volume prices trading_time
#> 1    1      4     10            0
#> 2    3      1     11            0
#> 3    4      4      8            0
#> 4    5      1     12            0
#> 5    9      4      7            0
#> 6   17      2     14            0
#> 7   18      4     13            0
#> 8   23      4      6            0
```

B.3 Developing with flexoptr

This library is developed and tested under R version 4.0.4 (2021-02-15). The library provides sophisticated functions for preparing data and optimising various pre-configured scenarios which are all natively documented. It is also possible to use the more basic functions and develop own scenarios.

B.3.1 Preparing Inputs for Simulations

The basis for most complex optimisations should be `optimise_schedule()`. Its inputs are however not self-explanatory because the function can be used very flexibly just by formatting them differently.

The logic behind the function assumes that a set of times should be optimised. For each time, there is one price present. By analysing the format of the price data, the function iterates over times where prices are present. As an example, the function `format_da_prices()` takes price data and formats them in a 24-step list which means that all 24-elements are traded and optimised simultaneously.

As a basic use case, one would want to compare the optimisation results of the same configuration of parameters but on different trading strategies. The function `simulate_marketing()` is a wrapper of `optimise_schedule()` that iterates through a day-ahead and intra-day marketing scenario.

At last, it is important to consider that the optimisation will only handle whole numbers as parameter inputs. By transforming the parameters but keeping the relation between the parameters equal, nearly any configuration can still be simulated.

B.3.2 Underlying Optimisation Algorithm

The whole simulation can be understood as a wrapper and input preparation for two basic functions, that comprise the optimisation logic of a constrained storage.

Description of physical constraints: The state and future needs of a storage can be described over three variables with a specific value for each time interval:

- Describing how much energy the storage will need to have charged to not be empty at the end of that time interval. In code, this value is described as `cummin`.
- How much energy can be possibly charged so that the storage would be full as fast as possible. This is referred to as `cummax` in code.
- Apart from the storage also the charging power is constrained, as it can only take values between zero and the maximum charging power. In contrast to the previous to variables it is described as `dirmax`.

The initially described `sample_constraints` are in fact a data.frame where one column describes each variable:

```
sample_constraints
#>    cummin cummax dirmax
#> 1       0      7      4
#> 2       0      7      4
```

```
#> 3         0      8      4
#> 4         0      9      4
#> 5         0     10      4
#> 6         1     11      4
#> 7         2     12      4
#> 8         3     13      4
#> 9         4     14      4
#> 10        5     15      4
```

Optimisation inside constraints: Beginning from a starting state and having calculated these three variables for the described points in time, a charge can be planned. The code first uses the constraints to make a selection of times where a change in schedule must and could happen:

- The first time (from a chronological point of view) that the `cummin` value is greater than one. Then, only that or preceding time intervals are a charge priority.
- Similarly, at value zero `cummax` describes that the charge cannot be increased at that point in time, or else the storage would charged beyond capacity at that or a later time.
- Finally, the remaining charging power `dirmax` must be greater than zero.

The optimisation itself is now a simply process of selecting the time with the lowest price out of the available prices and then adapting the constraints to reflect the change in schedule.

In the example of the `sample_constraints`, a selection would be made so that in the times 1-6 the minimal price would be searched. In the example at the outset the time 3 would then be chosen. As a consequence, the constraints are automatically adapted:

```
flexoptr:::adapt_constraints(sample_constraints, 3)
#>    cummin cummax dirmax
#> 1         0      7      4
#> 2         0      7      4
#> 3         0      7      3
#> 4         0      8      4
#> 5         0      9      4
#> 6         0     10      4
#> 7         1     11      4
#> 8         2     12      4
#> 9         3     13      4
#> 10        4     14      4
```

As a charge in time 3 happened, the values for `cummin`, `cummax`, and `dirmax` were all adjusted to reflect the new schedule. This process is repeated as often as units of charge are to be optimised. This approach (found in `optimise_constraints()`) thus takes into account the physical constraints when optimising for minimal prices.

Out of these building blocks, complex simulations are constructed by building constraints, optimising inside these constraints and then repeating these steps for consecutive time intervals (which is exactly what the function `optimise_schedule()` does).

B.4 Manual

The complete and detailled documentation can be accessed via the usual `?`-operator when the library has been installed. An automatically generated manual is appended to the print-out version of this document. This manual is also available on the online repository.

Erklärung zur selbstständigen Bearbeitung einer Abschlussarbeit

Hiermit versichere ich, dass ich die vorliegende Arbeit ohne fremde Hilfe selbständig verfasst und nur die angegebenen Hilfsmittel benutzt habe. Wörtlich oder dem Sinn nach aus anderen Werken entnommene Stellen sind unter Angabe der Quellen kenntlich gemacht.

Ort	Datum	Unterschrift im Original