Deduction of Emissions-, Exergy- and Price-Optimised Control Strategies for a Sector-Coupled District Energy System

Revision 1

by
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Foreword

With these words before the thesis I try to give you, the reader, an overview about:

- the persons who supported me during my writing process. (Acknowledgements)
- perspectives that should not stay unmentioned from my perspective in scientific documents in general or this topic in particular but are not the focus of my thesis. (Critical Opening Remarks)
- my writing style with regards to referencing, wording and the I-perspective. (Comments on Writing Style)
- a statement of mine concerning the preparation of this thesis by (only) me. (Declaration of the Author

Revisions

I indicate revisions on the title page and in the title of the (sub-)section where I change parts.

In the revised version 1, I change the figures on the results of validation and their analysis and interpretation. In the version before, the results for the class-definition-based and the classification-based priority lists were confused. These results are a part of the core of my thesis. Nonetheless, the core conclusions do not change. The results for both priority lists are well and therefore the main conclusions are valid still. In fact, the new results strengthen the conclusions. The class-definition-based priority lists yield better results (with one exception) than the classification-based priority lists. This strengthens the hypothesis that optimal priority lists can be deduced from model-optimal results - which is a fundamental hypothesis of my thesis and approach.

Acknowledgements

For me, life, work and in particular science are team work. To emphasise that, I start with my words of gratitude to people in my life.

At DLR - Institute of Networked Energy Systems (DLR-VE), I have worked in many teams: the institute DLR-VE, the division Energy Systems Technology, the working group Energy Management, the project group Energetic Neighbourhood District (ENaQ) and my office room partners. I highly appreciate the many meetings in the different settings we have had frequently, up to five meetings per week, as well as the informal meetings in between. I especially want to say thank you to Peter, my project leader, and my office room fellows Pedro, Alejandro and Moiz. I also want to express special thanks to two persons who supported me particularly much during my thesis:

Thank you, Patrik, for supporting me as my scientific supervisor with advice, discussions and, most important, a lot of time available for my questions.

Thank you, Herena, for supporting me as my technical supervisor. I highly appreciate your advice, discussions and the time available for my questions. I think that you are the person who I have learned of the most in the past two years. I learned from you about innovative teaching didactics (e.g. solar thermal online lectures), an open-door-policy, active listening (e.g. regarding the feedback regarding PPRE-courses), being the motor of a project (e.g. PPRE). And most important, about attitude and values as an engineer and as a person (e.g. open access, alternative funding of housing projects, energy cooperatives, feminism). In a highly men-dominated environment you stand

straight for you values, believes, ideas and projects and still manage to inspire students like me. You have been and are a role model for me. Thank you!

Addtionally, I want to express special thanks to my fellow PPRE-students and the PPRE-staff. I learned a lot from you, each and everyone, and I highly appreciate the learning environment the PPRE-family provides. I am grateful for every person that I have met in this programme in the last two years. I really think that the PPRE-experience, -network and -family is unique. PPRE is very valuable for me and I can say that PPRE will be part of my future, for sure. Thank you for being as you are, PPRE-family - full of wonders.

My motivation and energy is strongly linked to my network of friends and family. As I do not want to create hierarchies of more or less important members of this network, I would like to thank all of you for your support, friendship, time and love. This thesis would not have been possible without you. Windy hugs for all of you!

Critical Opening Remarks

I believe that every human being has a responsibility and power to shape the world we are living in. Science is not an objective or neutral sphere. Every time that I do not speak about discrimination and/or certain developments, I am not neutral but I am in favour of the discrimination or development. Based on this believe, I write these critical opening remarks in order to take over my responsibility against sexisms, racisms and the current price-oriented energy transition in Germany.

I am white, cis and a man. I state that in the beginning in order to use this chance to highlight discriminatory structures in the society I live in - and to position myself on the fully privileged side. I started studying in Oldenburg in PPRE with 24 students in total, 15 of them were men. None of them is non-binary or trans, to my knowledge at least. Out of the 15 course facilitators (e.g. lecturers) and academic supervisors I have had in PPRE, twelve are men and three are women. In my office room in DLR we are seven students, six men and one woman. In my project team at DLR, ENaQ, we are six persons, five men and one woman. PPRE is one of the few programmes at the university of Oldenburg for which we still pay study fees of 1 000 Euro/semester - having 22 out of 24 non-EU-citizens. This is not racism but discrimination of foreigners which is important to distinguish. There are many Black germans who experience racism. (Black is written with capital B as it is an empowering self-chosen name by Black persons, see also [1, p. 26].) But as many of my fellow students are non-EU-citizens, intersectionality of racisms and discrimination of foreigners is a big problem in my local environment. Sexisms (both against sexual orientations and identities) and racisms are, from my point of view, big problems in Germany, especially when they fall together - not only in my local

environment and as well institutional and structural as individual. Therefore, I want to raise awareness with this statement and encourage you if you are white, cis and/or a man: Inform yourself about sexisms and racisms in Germany (and globally). Stand up against sexisms and racisms. Reflect on the racisms and sexisms you reproduce yourself. Let us strive together for a more just and peaceful world that embraces diversity as enrichment. And I also want to ask for excuse for the racisms and sexisms that I reproduce myself in this thesis - e.g. via quoting many white men. I try to limit these reproductions as far as possible. If you read this thesis and notice racisms and/or sexisms, I would be very happy if you contact me and let me know so that I can learn to get rid of them. I am also very happy about any tips that could help me to reduce my own racisms and sexisms.

With the energy transition in Germany, the German government strives for greenhouse gas emissions reduction. From my perspective, this single focus combined with a market perspective on price is dangerous. Other to me important values such as political independency (e.g. imports from China/Russia), sustainable supply chains (e.g. mining for materials for batteries), postcolonial critics and regional economics (e.g. local photovoltaic panel production versus import from low-income-countries), economic and democratic participation (e.g. citizen energy versus big and stock market listed companies) and in general an economy oriented on democratically determined values beyond the price are either forgotten or deprioritised. Therefore, I want to make these values visible here. And ask you, the reader: Reflect on the importance of these values to you and stand up for an energy transition in Germany with more values than only greenhouse gas emission reduction.

Comments on Writing Style

In this section, I want to give an overview about how or why I use references, abbreviations, the I-form and the decimal point.

References after a point at the end of a sentence indicate a full sentence that is indirectly quoted. References after a number or the corresponding unit indicate that only the number is references whereas the rest of sentence does not have its origin in the reference. I also use page numbers for the references right in the text whenever possible so in case you want to trace an information back you can easily find it. In direct quotes I use *[...]* to specify that I leave out some original content or add some explanations *[that were not part of the original document like this]*.

I tried to build my work as much as possible on openly accessible references in order to make my research available and reproducible for as many persons as possible.

I use an overview in the beginning for all abbreviations but also indicate the abbreviations when used the first time in the text.

Throughout this thesis, I will use *I* and *my* whenever I write about something that I do or did. This shall help you to easily distinguish my work from the work of others that I reference and thus give merit to the ones whose work I use.

I use . as decimal marker.

For *highlighting*, numbers with the unit *[1]* and for dimensions (e.g. the energy E) I use italicised letters.

Declaration of the Author

I state and declare that this thesis was prepared by me and that no means or sources have been used, except those, which I cited and listed in the Recommendations for Further Research. The thesis is in compliance with the rules of good practice in scientific research of Carl von Ossietzky University of Oldenburg.

Oldenburg, November 9, 2020	
Place, Date	Author

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Abbreviations

A

AbLaV Abschaltbare-Lasten-Verordnung. 41

B

BBEn Bündnis Bürgerenergie eV. 4

C

Cbc COIN-OR Branch and Cut solver. 1, 9, 10, 20

chp combined heat and power. ix, 17, 21, 25–28, 32, 36, 42, 49, 51, 53, 54

D

dena German Energy Agency. 4

DLR German Aerospace Center. 73

DLR-VE DLR - Institute of Networked Energy Systems. ii, 5, 8, 13–15, 33, 34, 36–38, 41, 73, 74, 76, 77

E

E-LAB Energy Laboratory. 75

EEG Erneuerbare Energien Gesetz. 41, 42

ENaQ Energetic Neighbourhood District. ii, 3–8, 14, 15, 34, 36–38, 41, 55, 63, 65, 74, 76, 77

K

KPI Key Performance Indicator(s). xi, 6–8, 11, 14, 15, 20, 22, 23, 27–29, 31–33, 35, 40, 45, 52–57, 63–65

KWKG Kraft-Wärme-Kopplungs-Gesetz. 41

O

oemof open energy modeling framework. 1, 9, 10, 14–16, 18, 20, 22, 23, 31–33, 39, 60, 63, 64, 76

P

PPRE Prostgraduate Programme Renewable Energy. 8, 75, 76

pv photovoltaic. ix, 17, 18, 21, 22, 24–26, 28, 29, 36–38, 40, 41, 49–51, 53, 55, 65

Abstract

The goal of the thesis is to deduce emissions-, exergy- and price-optimised control strategies for a sector-coupled district energy system and assess their impacts on the greenhouse gas emissions. The research does not include mobility, does only include input data from 2017 until 2020 without future scenarios and does not include costs for anything else than operation, for example the social or environmental impacts of a local energy supply system over its full lifetime. For the research, two energy systems are modelled with the software tool open energy modeling framework (oemof). Both energy systems are optimised for operation with the solver COIN-OR Branch and Cut solver (Cbc) for emissions, relative exergy-input and prices. For one of these optimised operations, I deduce optimal control strategies. My approach is classification with priority lists as classes. For classification I use linear discriminant function analysis. I validate my deduced optimal control strategies with my energy system models in oemof with the priority lists as cost functions. It turns out that optimising operation for emissions instead of prices has a significant reduction potential for emissions. The deduced optimal control strategies perform well in the validation. A conclusion whether the deduced optimal control strategies are usable under real conditions cannot be drawn as the validation is done with oemof and therefore using information about the future which under real conditions will not be available. Also, the heat storages of the local energy supply systems are not steered by the deduced optimal control strategies but are optimised by the energy system model. In the end, recommendations for further research that would lead to holistic optimal control strategies that are usable under real conditions are given.

1 Introduction

As starting point of the thesis, I explain my motivation for the topic and the approach as well as the context of my thesis, the project ENaQ. I thereby want to embed the thesis in the context of national goals like the nationally determined contributions and the energy transition as well as the global goals from the Paris Agreement regarding the greenhouse gas emissions reduction. Building this foundation, I introduce my research question and guiding sub-questions, important research boundaries and the structure of the thesis.

In the first section, I deal with the questions: Why do I choose the topic of *a sector-coupled district energy system*? How does this topic matter in national and global contexts?

1.1 Motivation for the Topic: A Sector-Coupled District Energy System

In order to reach the 1.5 °C [2, p. 21] goal of the Paris Agreement global reduction of greenhouse gas emissions are necessary. The German government has set goals for its nationally determined contribution as greenhouse gas emission reduction targets in comparison to 1990 with -55 % for 2030, -70 % for 2040 and -80 to -95 % for 2050. [2, p. 28] Greenpeace concludes that in order to reach the goal of 1.5 °C without risking the necessity of carbon capture and storage, a reduction of the energy-related greenhouse gas emissions to 0 g/a in Germany is even necessary until 2035 [3, p. 3], Volker Quaschining claims it to be necessary until 2040 [4, p. 6] and that this is also achievable [4, p. 33].

In 2017, the source of 84.45 % of the greenhouse gas emissions in Germany were stationary and mobile energy activities which include fuel combustion as well as fugitive fuel emissions based on the Common Reporting Framework. [5, p. 68] Therefore, the most important measure to reach the reduction targets in Germany is the energy transition. For a successful energy transition in Germany, the renewable energy supply in the sectors of electricity, mobility and heat should be equally addressed. Whereas the renewable energy share in the electricity sector in 2018 amounts to around 37.8 % of the consumption, this share represents merely 13.9 % and 5.6 % in the heat and mobility sectors,

respectively. [6, p. 6] In order to reach the reduction targets, the share of renewables needs to be increased – especially in the heat and mobility sectors.

The German government has formulated many specific goals and measures to reach the reduction targets. [2, 32–77] Sector-coupling according to the German government can help decarbonising the energy demands in the heat and mobility sector as well as provide flexibility for the electricity markets. [2, p. 39] Sector-coupled district energy systems with regard to heat supply through electricity are specifically named as part of the German strategy. [2, pp. 48–49]

Others see benefits in sector-coupled district energy systems as well. The German Energy Agency (dena) sees the benefits of reduced greenhouse gas emissions in buildings as well as reducing the stress on electrical energy supply infrastructures through sector-coupling. [7, p. 57] The dena also sees benefits in decentralised energy supply such as reducing stress on electrical grids, reducing the demand for electrical grid extension, reduction of necessary investment in centralised energy supply and reduction of space usage. [7, p. 73] The *Bündnis Bürgerenergie eV (BBEn)* strives for a decentralised energy transition by citizens. [8] The *BBEn* sees the positive societal effects of a decentralised and citizen-driven energy transition in the integration into sustainable economic processes, an increased engagement within the energy sector, a higher acceptance for the energy transition, more participation, transparency and identity creation. [9] The authors of *Decentralised Energy – a global game changer* argue that through enhancing private ownership of the power sector the energy transition will be accelerated [10, p. 272] and have positive side effects like the empowerment to local, independent energy producers [10, p. 2].

Sector-coupling on a local and decentralised level is, thus, the obvious step for maximizing the synergies and benefits of both approaches for the energy system and to contribute to reach the 1.5 °C-goal. The 1.5 °C-goal could also be embedded as a contribution to the broader vision of Uwe Schneidewind: "[Die] kulturelle Vision der Nachhaltigkeit [...] [ist ein] gutes Leben für zehn Milliarden Menschen auf diesem Planeten [...] ohne die globalen ökologischen [oder planetarischen] Grenzen zu überschreiten". [11, p. 21] I translate this as: *The cultural vision of sustainability is a good life for ten billion humans on this planet without exceeding the global ecologic or planetary boundaries.*

A big challenge in sector-coupled district energy systems is the optimal control as these systems are highly complex. [12, p. 137] In this thesis, the focus is on control strategies. One reason for this is the context of the thesis, the ENaQ project. I therefore explain the context in the next section before I introduce the motivation for the approach of deducing optimal control strategies.

1.2 Context of the Thesis: The ENaQ Project

The ENaQ project develops novel concepts for a future-oriented energy management of a local energy system. Testing the energy system under real conditions is also future part of the project. As part of the sub-project *Networked Physical Infrastructure*, the DLR-VE takes part in the conception and planning of the physical infrastructure. A concept for the energy supply of the ENaQ at the former military air base in Oldenburg is developed, implemented and evaluated. The aim of the sub-project is a holistic view of the energy supply in order to identify optimization potential early and to be able to use it. The focus is on the sector-coupling of electricity and heat as well as the integration of mobility for individual houses and for the entire district.

In addition, the active co-design of the neighbourhood with future residents and interested people for future neighbourhoods will be pursued in the sub-project *Participatory Design*. The sub-project *Digital Platform* focuses on flexibility, security and technology openness. Core function is the provision of a largely automated local energy trading platform. Forecast-based energy management is used to implement load and procurement management with the local producers and consumers in the neighbourhood.

Given the topic and the context: Why is it necessary to determine control strategies for the ENaQ project? What shall they be optimised for? Where will they be deduced from - and why? These questions are the guideline for the next section.

1.3 Motivation for the Approach: Deducing Optimal Control Strategies

For a precise argumentation in this thesis, I distinguish between optimal operation and optimal control strategies. *Optimal operation* is the optimum with regard to a specific goal that can be obtained by simulation including data about the future that will not be available under real conditions. *Optimal control strategies* lead to an operation as close to the optimal operation with regard to a specific goal under as close to real conditions as possible. In the following, I introduce the optimisation and the deduction challenges which are the motivation for the choice of the approach.

The optimal operation of a district energy system depends on the goal(s) of the local project community. The ENaQ project has different goals. Different ways of operation are optimal in order to reach each of these goals. Therefore, the optimal operation for each of these goals needs to be determined. Different ways of operation of a sector-coupled district energy system can lead to different contributions to the energy transition in terms of reducing the greenhouse gas emissions. As an example from another than

the project of this thesis, a study on a district heating supply for two weeks in January through heat pumps with a thermal energy storage calculated the realisable emission reduction potential only due to operation to 20 %. [13, 10–15] The approach of zero emission neighbourhoods [14, p. 17] sets the focus away from optimal operation of the energy system and reduces the greenhouse gas emission reduction target to an energy balance problem. This leads to load-oriented consumption without considering the dynamically changing greenhouse gas emissions of the electricity from the grid, especially in winter. [15, p. 6] In this thesis, the dynamically changing greenhouse gas emissions of the electricity from the grid shall be considered.

The operation of the energy system determines the performance and interplay of the different system components. Determining the optimal operation for sector-coupled district energy systems is a complex, data and computational intensive task. This dependency on a great amount of data make control strategies for such energy systems a critical item for resilient operation. As the project infrastructure is not physically built yet, optimal control strategies that are based on a minimum amount of data need to be deduced from the simulation data on optimal operation.

In ENaQ, the optimal operation is determined by a linear optimisation model. This optimisation is done with data about the past, present and future. In this thesis, a method to deduce optimal control strategies for three KPI of the ENaQ project from the simulation data on the optimal operation is introduced. The KPI are greenhouse gas emissions, relative exergy-input and price. The choice of the KPI is further explained in *1.5 Important Research Boundaries* and *3.1.2 Reasons for the Optimization for the three KPI of ENaQ*. The effect of the deduced optimal control strategies on the sector-coupled district energy system ENaQ is also quantified.

Quantifying the effect of realisable control strategies that are optimal for different goals leads to a better understanding of the options for implementation of district energy systems. This understanding can then empower project developers to better inform and involve all relevant stakeholders and thereby increase the number of sector-coupled district energy system projects in Germany. Existing control strategies increase the capability for local operation that is independent of data-intense simulations and thus enhance a more resilient [16, p. 253] operation of energy systems. They would enable to transfer the obtained knowledge in form of the particular control strategies of one district energy system to another one and thus enhance the implementation of such distributed energy systems. More projects and more resilience of existing projects can accelerate the energy transition and thereby contribute to the greenhouse gas emissions reduction target of Germany.

Equipped with the topic, context and approach, in the next section you find the answers to the questions: What is the contribution of this research? Which questions shall be answered?

1.4 Research Question and Guiding sub-Questions

This master thesis project is devoted to deduce options for optimal control strategies for operation for a given system design within the ENaQ project and regarding the electrical and thermal energy supply. The research question is:

Which optimal control strategies can be deduced for the sector-coupled district energy system of ENaQ and what is their impact on the greenhouse gas emissions of ENaQ?

The following sub-questions are particularly relevant in the context of the master thesis:

1. Which optimal operations can be derived with the existing model from the chosen KPI for optimisation and what are the resulting greenhouse gas emissions for each optimisation?

2. Which method is most suitable to deduce an optimal control strategy from optimised model data that can be used under real conditions?

3. Which optimal control strategies can be deduced for the chosen KPI from the model data from 1) with the method from 2)?

4. How good are the simulation results obtained with the optimal control strategies that were deduced in 3) compared to the optimal operations from 1) in terms of KPI and greenhouse gas emissions?

Which parameters are considered to answer these questions? Which are outside of the research boundaries? These questions are answered in the next section.

1.5 Important Research Boundaries

This thesis is written in a time frame of six months. The broad topic and the limited time frame come with a need to set clear research boundaries which I make transparent in the following.

The energy for mobility services in ENaQ is not part of the existing model and will therefore also not be part of this thesis. The sector-coupling only refers to thermal and electrical energy.

The results of this thesis are based on the data for a reference year of the ENaQ project which is 2017. Other input data is only considered in a few boundary conditions for the

quantification of results - and then marked as such.

The options for optimisation are reduced to the defined KPI of the ENaQ project in order to stay close to the project implementation. The decision on particular KPI for the research in this thesis is based on a literature review and discussions with project members. The criteria for choosing KPI are availability of data, possibility for implementation in the given time frame and relevance for implementation of sector-coupled district energy system projects that aim to contribute to the energy transition in Germany.

The optimisation of the operation is based on an existing linear optimisation model at the DLR-VE and with the help of this built up from the scratch completely. The decision on the design of the energy system is not part of the thesis but is decided by project members at DLR-VE.

The choice of the method for deducing optimal control strategies from existing model data is based on the criteria accuracy of results as well as possibility for implementation in the given time frame.

Having introduced the topic, context, approach, research question and boundaries of the thesis, the next question is: How is this thesis structured?

1.6 Structure of the Thesis

To create a common ground of understanding, I explain the theory that I build my thesis on in chapter *2 Theory*. Here you can find the conventions that I apply and the scientific foundation that I believe in. In chapter *3 Methodology*, I explain the methodology and link my work to previous work at DLR-VE as well as to the theory that was built up by other scientists. The data I build up on is presented in *4 Data*. I present and discuss the results in one step in *5 Results and Discussion*. This again shall help to construct a clearly structured argumentation. The results are separately discussed for the optimal operation (5.1), the optimal control strategies obtained by deduction (5.2) and the simulated operation that results from the optimal control strategies (5.3). In *6 Conclusion*, I state my main findings, critically reflect my research and give some recommendations for further research. Right behind my *References*, I added information about the DLR-VE, Prostgraduate Programme Renewable Energy (PPRE), give some insights in my writing process and summarise some personal lessons I have learned within this process.

How does optimisation in simulations work according to other scientists? And what they say with regard to deduction for optimal control strategies? By answering these questions I build the theoretical foundation for my thesis in the next chapter.

2 Theory

In this chapter, I introduce the theoretical framework on which I base my work on. I start with the theory that I use to optimise operation (2.1) and continue with the theory I need to deduce optimal control strategies (2.2).

2.1 Optimisation of Operation

In order to optimise operation, I use theory of others for two major parts of my work: the model and the solver of the model. The model I use is *oemof* which I introduce in subsection 2.1.1. My solver, *Cbc*, I explain in subsection 2.1.2.

2.1.1 The Model: The Open Energy Modeling Framework (oemof)

To model my energy systems, I use the python package oemof. oemof is introduced by its developers as "a single energy modelling framework" that shall "foster open science in the field of energy modelling and analysis". [17, p. 2] The authors highlight the oemof-features "collaborative development with the goal of community building", a "generic data model" that enables researchers to have a look on both, particular power plants and huge energy systems, a "multi-purpose toolbox" to which own features can be added and a "strict open source [...] philosophy". [17, pp. 5–18]

In oemof, an energy system is a system of directed graphs built by "nodes" which are connected by "edges". [17, pp. 7, 11–13] From these directed graphs, oemof can create mixed-integer linear optimisation problems. [17, p. 8]

oemof is writen in Python and a package. [17, p. 10] It builds on other packages like *pyomo* for optimisation problems and *pandas* for data processing. [17, p. 13]

For application, the framework of oemof consists of various libraries that can be used for different purposes and included as modules. [17, pp. 14–15] In order to create the mixed-integer linear problem for optimisation, the *solph*-library is needed.

The oemof-documentation of the latest stable version can be found in [18].

2.1.2 The Solver: COIN-OR Branch and Cut (Cbc)

To solve the mixed-integer linear problem for optimisation, oemof uses solvers. I use the solver Cbc ([19]) which I want to introduce in this subsection. Cbc is open-source and written in *C++*. [20] It solves the mixed-integer linear problem by branching, bounding and cutting.

Branching means to split the problem in simplified sub-problems, "branches", which are added as "nodes" to the "search tree". [20] Bounding means to find upper limits (any valid solution) and lower limits (through problem relaxation) and thereby identifying branches of the search tree that are not optimal. [20] Cutting means to identify inequations with which the lower limits from problem relaxation can be brought closer to the solution space. The system of equations grows in this step by inequations and is solved again. The new solution helps to cut non-feasible solutions from existing nodes or even branches in the search tree. This is referred to as "tighten" the linear problem relaxation. [20]

According to the introduction ([20]) of Cbc, Cbc works, simplified, in six steps: First, it bounds and cuts the possible solutions. Secondly, it branches. Until the search tree is not empty, it then repeats the last four steps. Choose a node, re-optimise the linear problem, bound and cut and then branch again.

For further details on the solver, the Cbc-documentation can be found in [20].

2.2 Deduction of Optimal Control Strategies

For deducing optimal control strategies, I use classification as my approach and linear discriminant function analysis as my method. Classification is introduced in subsection 2.2.1 and linear discriminant function analysis in subsection 2.2.2.

2.2.1 The Approach: Classification

Classification is distinguishing two or more unknown groups and then assigning new data to one of these groups. [21, p. 231] In contrast to clustering, the groups are already known. [21, p. 231]

"The challenge in classification modeling is dealing with the misclassification rate of objects [...]." [21, p. 231] How I deal with this challenge, I argue in section 3.2.

In my thesis, I deal with *parametric* classification approaches. *Parametric* classification approaches rely on assumptions about the data distribution in contrast to non-parametric classification approaches. [21, p. 243]

2.2.2 The Method: Linear Discriminant Function Analysis

In linear discriminant function analysis, the goal is to identify "a linear model from a set of [...] observed quantitative variables". [21, p. 235]

$$z = w_1 * x_1 + w_2 * x_2 + .. + w_i * x_i \tag{2.1}$$

$$\max \left(\frac{squared\ distances\ between\ means\ of\ z}{variance\ of\ z} \right) \tag{2.2}$$

Each observed variables gets a weight. Like this, "multivariate observations" are "converted into univariate observations" (see Equation 2.1 for a number of i steering parameters and weights). [21, p. 235]

The goal of linear discriminant function analysis is to "maximize the ratio of between-class scatter to the within-class scatter" (see Equation 2.2). [21, p. 235]

The concrete algorithm for linear discriminant analysis from *Scikit-learn* that I use is based on a *Gaussian density* and *Bayes rule.* [22]

How does the model of the energy system look like? Why do I choose the presented three KPI for optimisation? And, most important, the second guiding sub-question of this thesis: *Which method is most suitable to deduce an optimal control strategy from optimised model data that can be used under real conditions?* How do I validate the deduced optimal control strategies? These questions are answered in the next chapter.

3 Methodology

In this chapter, I explain the methodology I use as well as how it connects to previous work at DLR-VE and theories from other scientists.

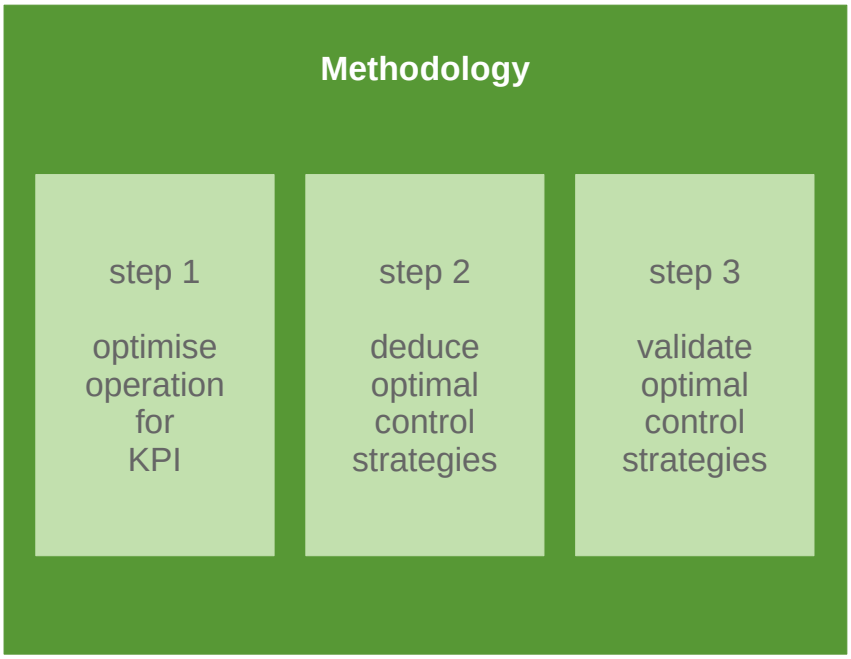

Figure 3.1: overview of the methodology

As shown in Figure 3.1, I split this chapter in three sections. For each section, I describe the concrete results that I expect to obtain.

The first section (3.1) is focused on optimal operation. I explain how I optimise the operation, which data is needed as input and which outputs I generate.

In the second section (3.2), I explain how I deduce the optimal control strategies from

the model results for optimal operation. This section contains the answer to my second guiding question and describes how I obtain an answer to my research question.

In the third section (3.3), I make transparent how I validate the obtained control strategies based on a comparison of simulation results.

3.1 Optimise the Operation through Simulation

In this section, I deal with the *how* of the optimisation of the operation through simulation. I firstly explain the choice of *oemof* as simulation tool (3.1.1) and the three KPI (3.1.2). The optimisation of the operation is made for two design scenarios which I present in 3.1.3. The optimisation of the operation is then presented in two parts regarding the model itself (3.1.4) and the optimisation of the model with costs in oemof (3.1.5). Finally, I summarise the relevant output of the optimisation (3.1.6) from which I afterwards deduce the optimal control strategies (3.2).

3.1.1 Reasons for the Simulation with the Modelling Framework oemof

As I am part of the ENaQ-project, I work with the same modelling framework as my colleagues at DLR-VE in order to increase re-usability and comparability and to build upon previous work. The choice of oemof for the ENaQ-project at DLR is argued in [23, p. 10]. This choice is also in line with the open science position with regard to software [24] of the Helmholtz-community of which DLR-VE is a part: to promote open science solutions also in terms of open source software.

None of the analysed proprietary software options from [25] meets the requirements of the ENaQ-project. [23, p. 10] A self-developed solution from the scratch would come with high risks on the quality of the solution and huge development needs. [23, p. 10] The solution that is closest to the requirements of the ENaQ-project is oemof. [23, p. 10] The main advantages of oemof over other open-source alternatives are that it is "tested and valid", "continuously developed" and "relatively easy to use". [23, p. 10]. Not all of the requirements of the project were already met at the start of the ENaQ-project at DLR-VE. Due to its open-source character, the missing components and parts could and can be added by code from DLR-VE.

3.1.2 Reasons for the Optimization for the three KPI of ENaQ

For both, optimising of operation and deducing optimal control strategies, I need optimisation criteria. As this thesis contributes to the ENaQ-project, I decided to stay as close to the KPI of the ENaQ-consortium as possible. The KPI of the ENaQ-project of the consortium are documented in [26].

The whole ENaQ-project is split into three topic areas. The DLR-VE is part of the topic area "physical infrastructure". In total there are 29 indicators for this topic area. Each indicator for me means two model optimisations, one for each scenario. So, there is a need for me to further reduce the number of indicators.

Within the topic area of physical infrastructure, there are four indicator categories: resource consumption, prices, energy supply and mobility. Mobility is out of my research scope - so I do not evaluate indicators in this group. I also decide not to have a look on the indicators in the category energy supply as most of the indicators here are stronger influenced by the system's design, not by the operation.

Each category has leading indicators. For resource consumption this is greenhouse gas emissions, for prices this is energy purchase costs from a consumer's perspective. As these are the leading indicators, I choose both of them for my research.

Additionally, there already has been exergy research in the project-group of ENaQ at DLR-VE. [27] Relative exergy-input is also one of the indicators in the category resource consumption. In order to build on previous work and continue with it, I decide to also optimise on exergy-input.

In order to measure emissions in tonnes of CO_2-equivalents, prices in *Euro* and exergy-input in *MWh*.

I measure my indicators in different units than it is done by the ENaQ-consortium. There, the indicators are normalised by person and year. I also implicitly normalise by year as I model with one year of input data. Then, I do not normalise by person but by total energy demand in *MWh*. Thereby, I try to make my results easier comparable to values from other projects. The demand-normalisation also helps to make the results on the exergy-input easier interpretable.

Equipped with these reasons for the modelling environment oemof and the KPI (emissions, exergy-input, prices), I now explain the design of the two modelled energy systems.

3.1.3 The Design of the two Modelled Energy Systems

I deduce optimal control strategies for two energy system design scenarios. I decided to have a more conservative, fossil-based scenario and a more ambitious, renewable-based scenario. With conservative in this context I refer to closer to real, existing applications and energy system designs and therefore closer to the price-optimum in the last years. The design of the two energy systems is not part of the optimisation in this thesis. Nonetheless, I want to give arguments for the technologies chosen in the different scenarios in this subsection. The energy systems are then modelled in oemof (see 2.1.1 for further explanations on the modelling in oemof). In *4 Data*, I also want to give an overview, arguments and references for the sizes of the plants and other parameters. The core of both scenarios is a local energy supply system. This system has connections to the grids and the supply which are outside of the system itself. Inside of the system are the local energy conversion technologies and many connections. I start with presenting the fossil-based scenario.

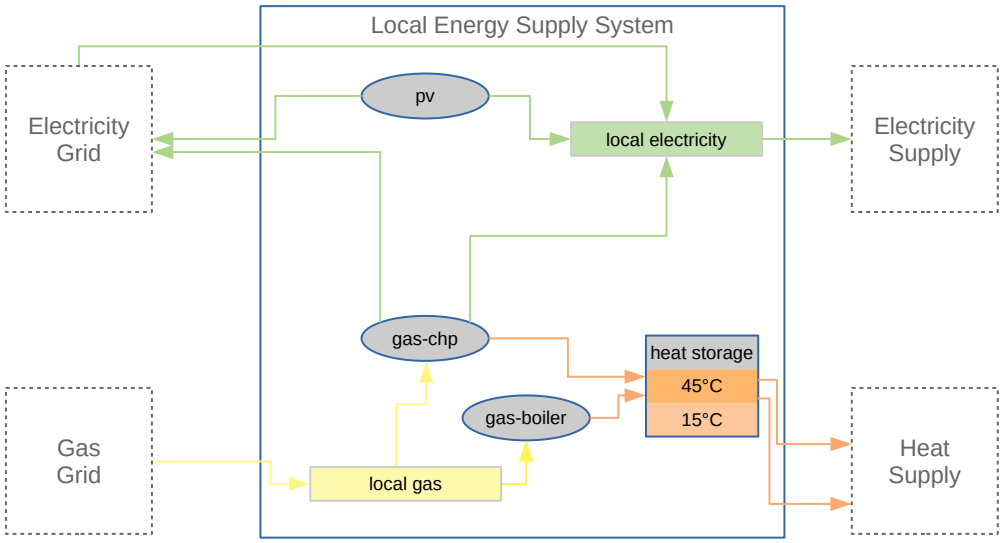

Figure 3.2: energy system design - fossil-based scenario (overview)

The local energy supply system in the fossil-based scenario has connections shown in Figure 3.2 for gas imports, electricity imports and exports, supply of electricity and heat

demand are shown. The heat demand is connected via two energy flows at it consists of the heat demand for heating and warm water.

Inside of the system are the technologies which in the fossil-based scenario are a pv power plant, a chp plant powered by gas, a boiler powered by gas and a heat storage.

The electricity from pv and gas-chp can be exported or used to supply the demand. The electricity demand can also be supplied by grid electricity.

The heat demand can be supplied via the chp plant or the boiler. In the fossil-based scenario, both heat demands for heating and warm water are supplied at 45 °C as the temperature level does not matter neither for the chp plant nor for the boiler. Additionally, the heat can be stored in a stratified heat storage with 2 temperature levels, 45 °C as upper and 15 °C as lower temperature level.

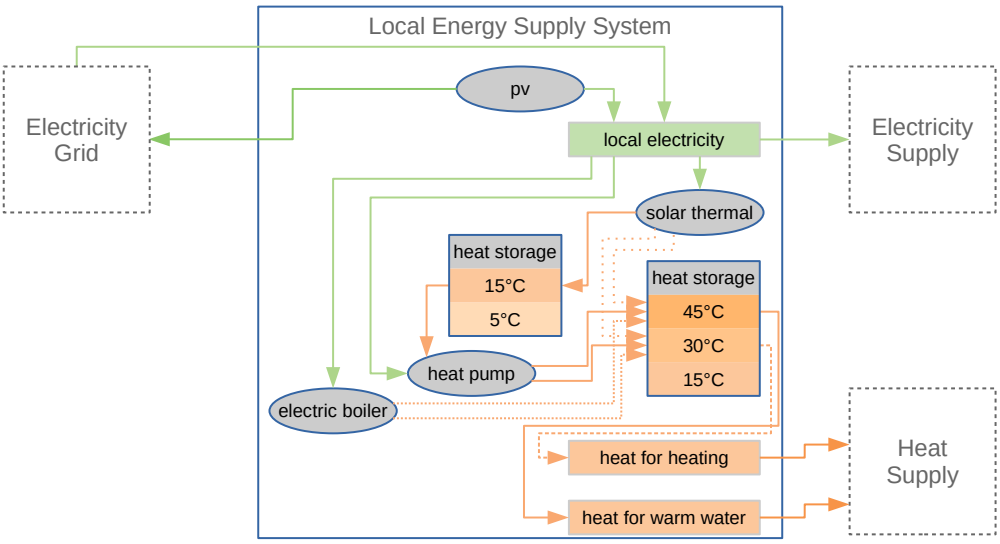

Figure 3.3: energy system design - renewable-based scenario (overview)

In the renewable-based scenario (Figure 3.3), there is no connection to the gas grid. The other connections outside of the local energy supply system stay the same.

The technologies in the renewable-based scenario are a pv power plant, a solar thermal power plant, a heat pump, an electric boiler and two heat storages.

In the renwable-based scenario, the electricity demand can be supplied via pv and grid electricity. The electricity from the pv power plant can also be exported.

The heat demand is supplied at two temperature levels: 45 °C for warm water and 30 °C for heating. The electric boiler can supply heat at both of these temperature levels. As I optimise the model with the solph-package of oemof for energy, I cannot model variable temperature levels for the solar thermal power plant. In order to still model different operational states, I choose three temperature levels as temporarily static operational state of the solar thermal power plant. The solar thermal power plant can supply heat at 15 °C, 30 °C or 45 °C. The heat from the solar thermal power plant at 15 °C can be converted to 30 °C or 45 °C with the heat pump or stored in a stratified heat storage with two temperature levels, 5 °C and 15 °C. For the heat at 30 °C and 45 °C, there exists another stratified heat storage with three temperature levels, 15 °C, 30 °C and 45 °C.

3.1.4 Constraints of the Renewable-Based Model in oemof

Using oemof for the optimisation comes with some constraints for my model of the renewable-based scenario. These constraints lead to a slightly different energy system setup in the model than in the concept I explained before which will be important for the optimisation via costs that I explain in 3.1.5, the deduction that I explain in 3.2 and the analysis of the results (5). In this subsection, I want to explain these constraints and the resulting energy system design in oemof.

In Figure 3.4, the comparison of the solar thermal power plant in the renewable-based scenario between reality and oemof is shown. As pointed out before, I cannot model variable temperatures for the solar thermal power plant. Still, I can model three different steady temperature levels at the output as operational states. I can do so by modelling three solar thermal power plants with the same parameters but different input and output temperatures. These three solar thermal power plants are represented by the three triangles marked with different temperature levels at output in Figure 3.4. In my model, the three solar thermal power plants have a common source that they share. Conceptually, it might be thought of as a representation of the radiation. This way, I model that within a time step the operational mode may be switched and supply at different temperature levels within one time step is possible.

The same thing as for the solar thermal power plant counts for the heat pump. In Figure 3.5 the comparison is shown: the one heat pump in reality is modelled by two heat pumps in oemof represented by the circles in Figure 3.5 and marked with the respective output temperature level. Both heat pumps have the same parameters, in

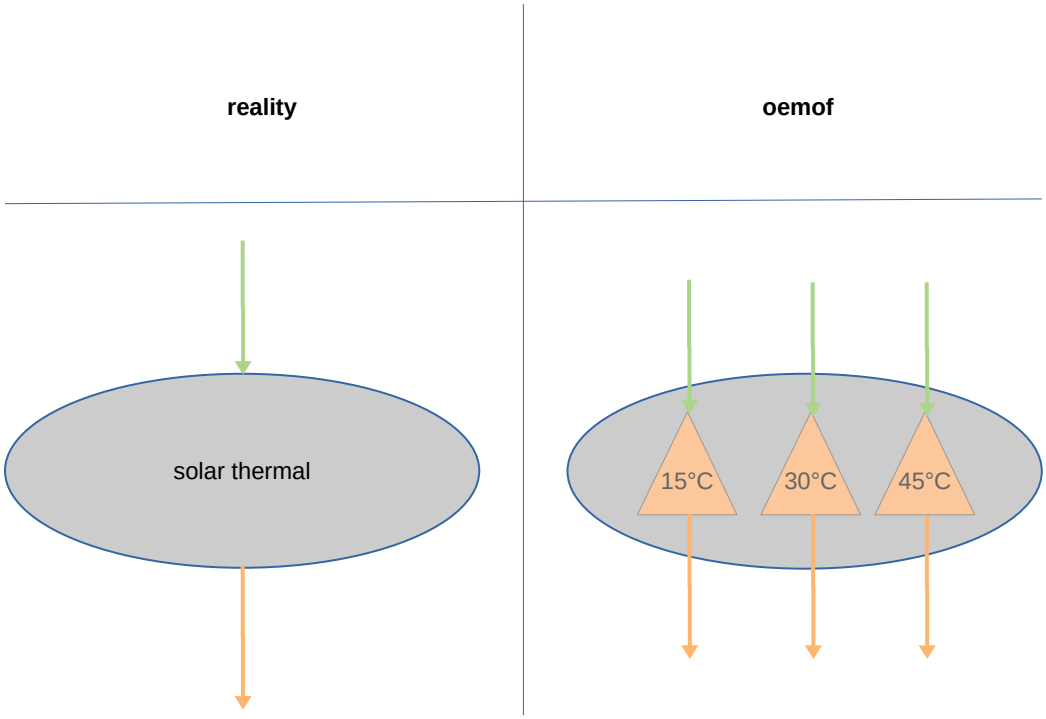

Figure 3.4: solar thermal power plant - representation of reality in oemof (green arrows for electricity flows, orange arrows for heat flows)

this case even the input temperature is constant at 15 °C from the solar thermal power plant. The different temperature levels at the output lead to different coefficients of performance. In the case of the heat pumps, there is a common electricity input so that switching operational modes within one time step is possible.

Limiting the heat flows to only be at 30 °C or at 45 °C and having at the same time energy demands that are supplied at different temperature levels comes with another model extension: I need to make energy flows between the two temperature levels possible. This enables for example to supply the heating demand with heat at 45 °C if enough heat is available, for example for the solar thermal power plant. Heat at 45 °C cannot be directly supplied by heat at 30 °C. Nonetheless, the heat that is needed to increase the heat storage temperature from 15 °C to 30 °C can be supplied by the solar thermal power plant or the heat pump in the respective operational state and than be combined with heat from the electric boiler to supply the full heat demand for warm water at 45 °C. This becomes important when I analyse the resulting energy flows in the model optimisation and is therefore explained here.

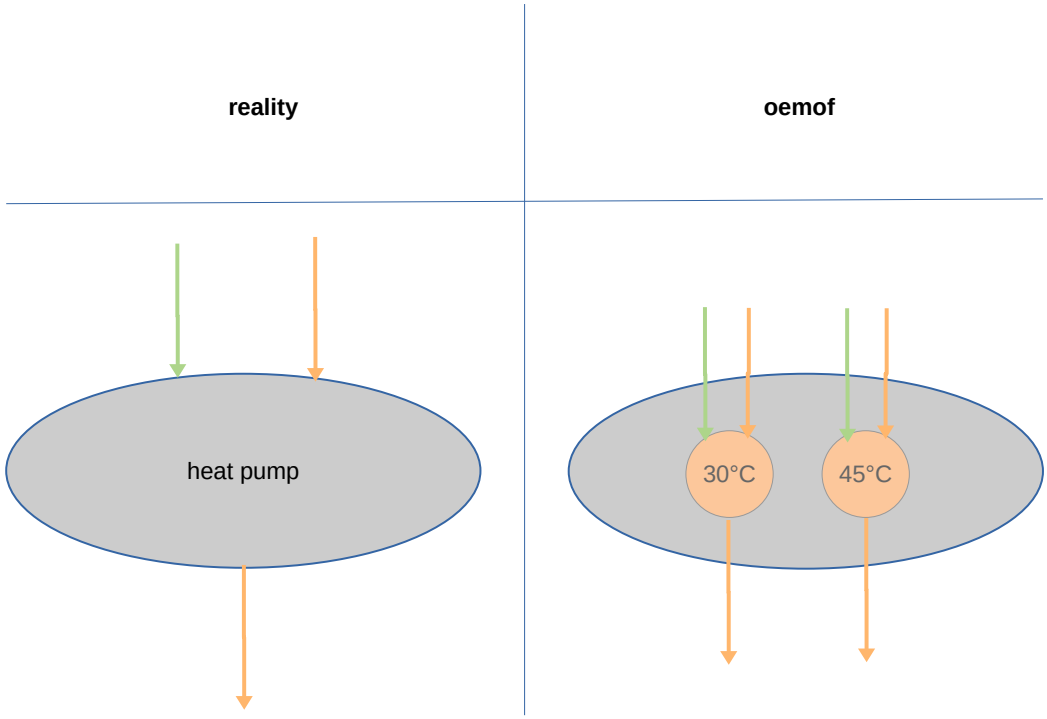

Figure 3.5: heat pump - representation of reality in oemof (green arrows for electricity flows, orange arrows for heat flows)

3.1.5 The Optimisation of the Operation with Costs

The energy system model in oemof is optimised by a cost function. I therefore set the boundary conditions for the energy system like a fixed demand, maximum capacity of the power plants and all other input data. Then, I assign costs to some energy flows. These costs are KPI-specific: emissions, exergy-input or prices and always per unit of energy in the particular flow. The model is then optimised through the cost function with the goal of minimising the costs with the Cbc-solver (see 2.1.2 for further explanations on the solver). Having different costs for the different KPI leads to different energy flows and operation of the power plants. In the following, I want to present the energy flows that I put costs on. Not all costs in both scenarios are needed for all KPI - not needed costs are zero for the particular optimisation.

In Figure 3.6, I present the conceptual overview of the costs in the fossil scenario. The costs of grid imports of electricity may be emissions of the grid's electricity, the exergy-input for one unit of grid electricity or prices. The revenues for selling electricity or heat

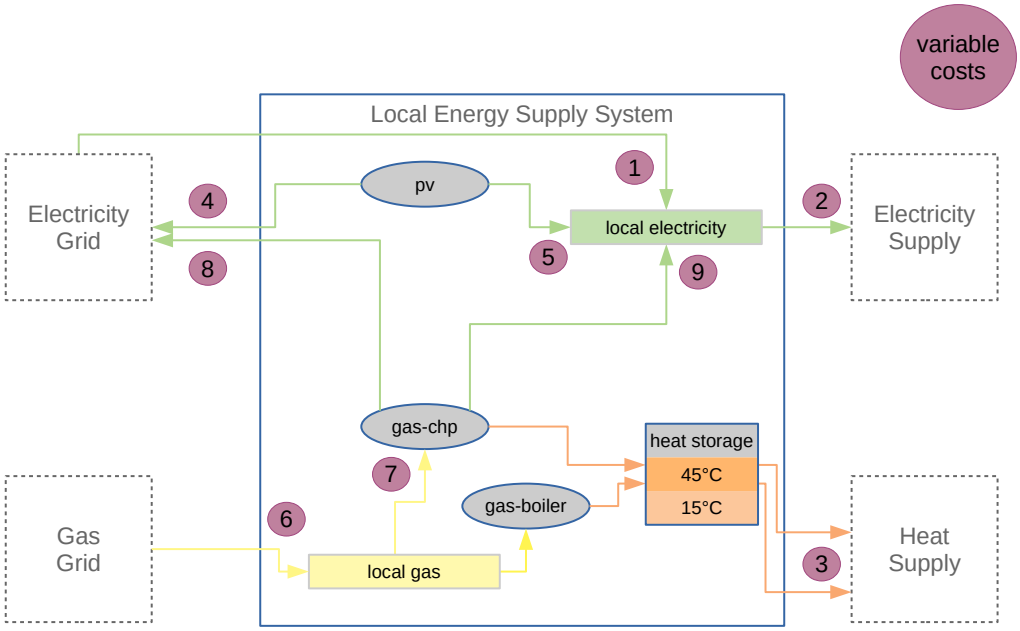

Figure 3.6: costs in model-optimisation of fossil scenario - conceptual overview (*1*: imports of electricity, *2*: revenues for selling electricity, *3*: revenues for selling heat, *4*: revenues for selling electricity to the grid from pv, *5*: local electricity supply of pv, *6*: gas imports, *7*: chp-specific costs, *8*: revenues for selling electricity to the grid from chp, *9*: local electricity supply of chp)

for both heating and warm water to the households are only relevant for prices and fix as the demands are fix as well. The revenues for selling electricity to the grid from pv and chp are only relevant for prices. I do not consider any savings in the emissions or exergy of the grid from exports of electricity in the results for the district. chp-specific costs are costs in terms of prices and reflect on chp-specific subsidies.

In Figure 3.7, I present the conceptual overview of the costs in the renewable scenario. The costs *1* to *5* stay the same as for the fossil scenario. The gas-specific costs do not exist anymore. Instead, the costs *6*, *7* and *8* reflect on the different costs in terms of exergy-input for the heat from the solar thermal power plant in dependence of the temperature level - all of them being below the costs for pv in order to prefer solar thermal heat over heat from pv through the electric boiler. Heat at lower temperature comes with lower costs in terms of exergy-input as well. The goal of this is to optimise for

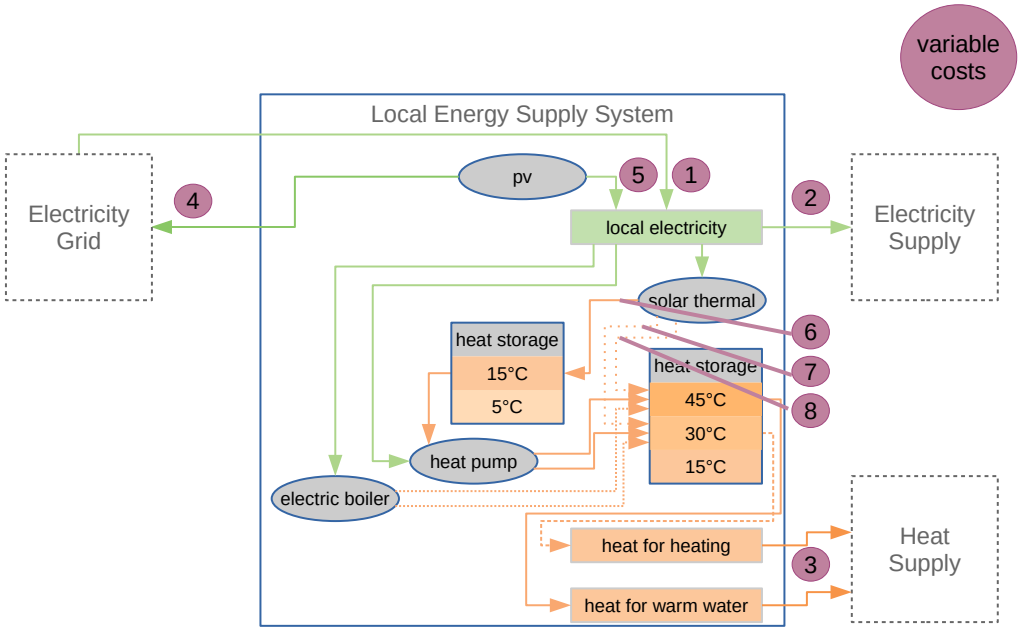

Figure 3.7: costs in model-optimisation of renewable scenario - conceptual overview (*1*: imports of electricity, *2*: revenues for selling electricity, *3*: revenues for selling heat, *4*: revenues for selling electricity to the grid from pv, *5*: local electricity supply of pv, *6* to *8*: temperature-specific costs for heat for solar thermal power plant)

lower exergy in order to minimise the losses in the heat supply grid and and to maximise the solar thermal power plant operational time. As the grid losses are simplified in my model, losses under real conditions can be bigger. Therefore, explicit costs in terms of relative exergy-input are necessary and the pure optimisation based on the energy output is not enough in this case. In terms of emissions and prices these costs are irrelevant.

I have now given the reasons for both choosing oemof to model my energy systems and the KPI emissions, exergy-input and prices and optimisation goals. I have explained the design of the two energy system designs for the fossil and the renewable scenarios, including the constraints for the renewable scenario. I also stated how the objective function is built with costs at different energy flows. But what are the results that I expect to obtain from optimising operation?

3.1.6 Expected Results for Optimised Operation

The optimisation of operation shall deliver two results: the KPI-results for the optimisations for both scenarios and the foundation for deducing optimal control strategies. For each scenario, I want to obtain three optimised operations, one for each KPI. For each of these optimised operations, get a resulting value for all three KPI. Therefore, I get a three times three matrix with the KPI-results for each KPI for each scenario. From this, I can identify the potential of optimising the operation for a particular KPI.

From these optima, I try in a second step to deduce optimal control strategies that are under real conditions usable, well-performing and resilient. How do I deduce optimal control strategies from the results from the optimised operation that I obtained with my oemof-models? Which are the results that I want to get with this deduction? These are the guiding questions for my next section.

3.2 Deduce Optimal Control Strategies from Optimal Operation

In this section I answer my second guiding sub-question: *Which method is most suitable to deduce an optimal control strategy from optimised model data that can be used under real conditions?*

I only deduce optimal control strategies for the fossil-based scenario as this scenario is less complex than the renewable-based scenario but thereby it is already possible to show the method.

I decide to use classification for my deduction of optimal control strategies based on [21, pp. 231–252]. In my case, the classes need to be categorical whereas my steering parameters can be both, categorical or continuous. [21, p. 234]

The starting point of this section are the results from the optimised operation. At first, I define my classes as priority lists (3.2.1). Having identified the priority list for each time step in the results of the optimised operation, I explain how I identify my steering parameters to classify each time step in order to obtain a under real conditions usable control strategy from my operation results (3.2.2). In a third part, I describe the results that I expect to obtain (3.2.3).

3.2.1 Definition of Classes as Priority Lists

Priority lists as classes have the huge advantage that dealing with misclassification gets easy - which is a great challenge of classification (see subsection 2.2.1). Firstly, I do not risk to not supply the demand, as all technology options are taken into account for each point in time. Secondly, I do not steer the technologies depending on non-control-parameters of this technology and therefore do not need to deal with contradictory control signals, like a pv plant being instructed to supply electricity due to irradiance available but at the same time having technical problems and not being able to supply. In this case, my control strategy would need to re-organise the control signals for the other technologies as well. With the priority lists, I instead first access the availability information and then assign priority numbers to each technology to supply depending on the current demand. How this works and how I obtain the priority numbers is explaiend in the following.

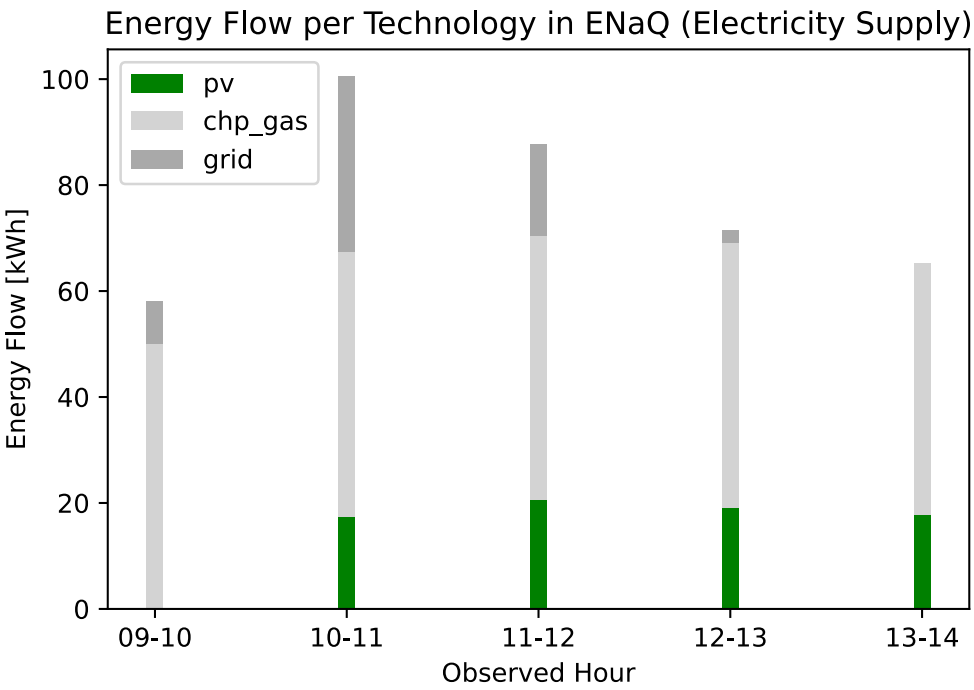

Figure 3.8: energy flows from optimised operation (example: fossil-based scenario)

The starting point of my deduction are the model results from optimised operation, specifically the resulting energy flows. In Figure 3.8, I show exemplary result data for some hours of a day in the fossil-based scenario that was optimised for emissions. In the figure, energy sums for a particular hours are shown. I use hour-specific time series data

on energy, not on power. The figure does not show energy over time but energy sums for particular hours. Therefore, I do not plot technology-specific, continuous lines and areas but bars. The total energy demand differs from hour to hour, in this case within 50 kWh and 100 kWh. The supply technologies also change from only chp and grid over pv, chp and grid to only pv and chp.

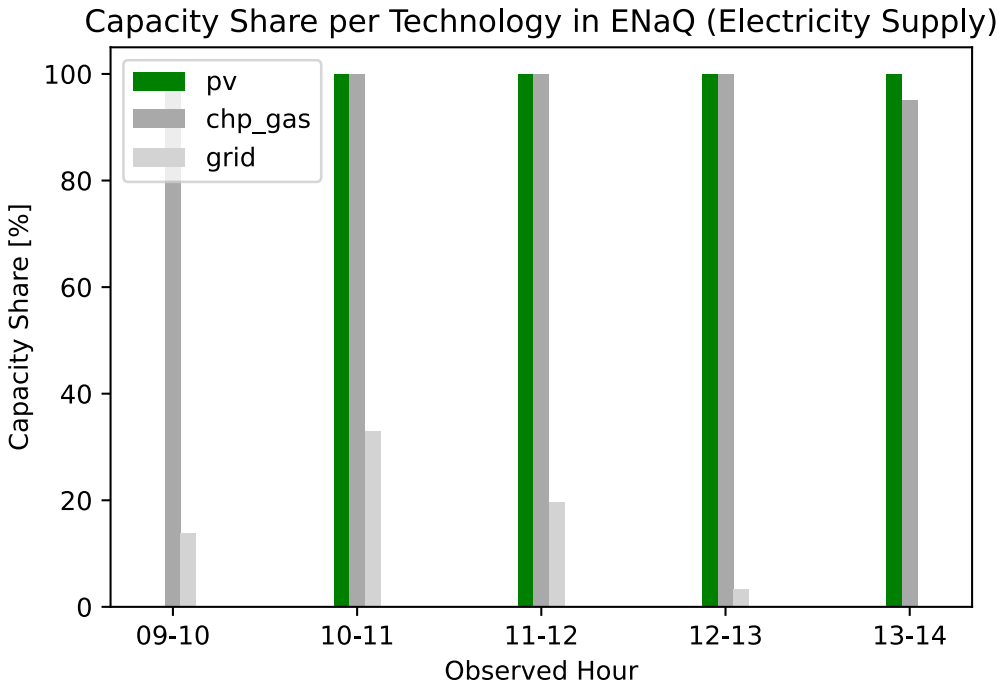

Figure 3.9: capacity shares based on energy flows (example: fossil-based scenario)

The energy flows from Figure 3.8 are then transformed to the capacity shares shown in Figure 3.9. The capacity shares are values from 0 % up to 100 % that indicate how much of its potential a technology supplies to the local demand for a given time step. For pv, the capacity is a time series depending on the irradiation. If there is no irradiation, the capacity for pv is set to a very high number in order to identify these special circumstances. For chp, the capacity is a fixed value in terms of installed capacity. For the grid, the capacity is the demand.

These capacity shares shall help to identify which of the technologies is prioritised by the optimisation in each hour. For my example, the resulting priority numbers with *1* being the highest priority of each technology for each hour are shown in Table 3.1. In this case, different energy flow situations and different capacity share situations are defined as belonging to the same priorities, therefore the same priority list and the same class.

Priority Number (1 is highest) per Technology in ENaQ (Electricity Supply)			
Observed Hour	pv	chp	grid
09-10	1	2	3
10-11	1	2	3
11-12	1	2	3
12-13	1	2	3
13-14	1	2	3

Table 3.1: priority numbers based on capacity shares (example: fossil-based scenario)

This does not necessarily have to be the case. In the following I want to explain how I assign different situations in the energy system in terms of different capacity shares of the different technologies to technology-specific priority numbers.

Possible Classes as Priority Lists (Electricity in Fossil-Based Scenario)			
Class	pv	chp	grid
class 1	1	2	3
class 2	1	3	2
class 3	2	1	3
class 4	3	1	2
class 5	2	3	1
class 6	3	2	1

Table 3.2: possible classes as priority lists

I start by defining all possible classes in the form of priority lists. These classes are scenario-specific and specific for heat or electricity supply. In Table 3.2, I have shown the example of the electricity supply for the fossil-based scenario. If suitable, I already reduce the numbers of classes at this stage. For the given example, the *classes 5 and 6* do not need to exist both as if the grid is preferred, it can for sure provide the full demand. The second or third priority do not matter. So, I already reduce the classes before assigning certain conditions of the energy system to them.

Having this set of classes, I start defining all possible conditions. A condition for me is a certain set of capacity share combinations. An example for a condition in the electricity supply of the fossil-based scenario is full-load supply of the chp plant, part-load supply of the pv plant and no supply from the grid. Part-load of the pv plant refers to some of its energy being exported to the grid. I define conditions until all my data points are assigned to one of the defined conditions.

The defined conditions for the electricity of the fossil-based scenario including the classes they are assigned to are shown in Table 3.3. I assign the conditions 1 first, based on the resulting relative frequencies of the classes the conditions 2 and step by step up to the conditions 5. I assign the conditions step-wise because the priority lists (in the

table shown as classes) are not clear for all conditions - which I explain with an example in one of the following paragraphs. I document the reasons to choose a class for a certain condition right in the code which is available in my git repository. I define more conditions than are shown in the table but these are the conditions that actually occur in the optimisation results of the fossil-based scenario.

For the heat, I define that heat from the gas-powered boiler is only preferred if there is no heat supplied by the gas-powered chp and at least some heat supplied by the chp. In all other cases, the gas-powered chp is preferred.

Conditions and Their Classes (Fossil-Based Scenario, Electricity)				
Condition	Share pv	Share chp	Share grid	Class
Condition 2a	$x = 1$	$0 < y < 1$		1
Condition 4a	$x = 1$	$y = 1$		1
Condition 4b	$0 < x < 1$	$0 < y < 1$		1
Condition 5a	cap. $= 1e^{12}$	$0 < y$		1
Condition 3a	$0 < x$	$y = 0$		2
Condition 5b	cap. $= 1e^{12}$	$y = 0$		2
Condition 2b	$0 < x < 1$	$y = 1$		3
Condition 3b	$x = 0$ and cap. $!= 1e^{12}$	$0 < y$	$z = 0$	3

Table 3.3: definition of conditions of capacity share combinations with the shares of pv (x), chp (y), grid (z) and the capacity of pv (cap.) and the respective classes

Conditions and their Relative Frequencies for only Conditions 2	
Condition	Relative Frequency
Class 1	12.6 %...15.9 %
Class 2	0 %
Class 3	0.0 %...3.1 %
Class 4	0 %
Class 5	0 %
Not Assigned	12.6 %...81.0 %

Table 3.4: relative frequencies after assignment of conditions 2 (fossil-based scenario)

I want to give an example for the process of assigning the conditions to classes step by step. After assigning the conditions 2, I get relative frequencies for the classes to which I assigned the conditions for a particular KPI as shown in the example of Table 3.4. I show relative frequency ranges as the relative frequency of a class depends on the optimisation goal and is therefore KPI-specific. Deviating from the classes in Table 3.2, I deleted the *class 6* as explained before and added a line for the not-yet-assigned conditions.

With the help of these relative frequencies, I then argue for the class-assignment of the

conditions 3. For the condition 2a, it is clear that pv is preferred over chp as otherwise chp would be in full-load and pv in part-load. For condition 4a instead, it is less clear: If both, pv and chp are in full-load, which of them is first and which is second priority? By analysing the relative frequencies of the classes for only the conditions 1 and conditions 2, I can argue for the class-assignment of these pv- and chp-full-load-cases with the relative frequencies of, for example, the conditions 1 and conditions 2. The result of these assignments is shown in Table 3.3.

Having all conditions assigned to a class, I get priority numbers for all time steps (Table 3.1) and the relative frequencies of all defined classes for my example. The results are specific for the fossil-based scenario, electricity or heat supply and the KPI chosen as optimisation goal.

I want to add two critical comments: Firstly, I ignore the heat storages for both scenarios in this priority assignment. With my priority lists I can only make decisions on the energy supply. For the heat storages, it would be necessary to not only identify the discharge but also the charging times. For a first approach, I want to use the priority list with the highest relative frequency to all time steps. Therefore, I cannot assign priority values to the heat storages. For further improvements with more classes and not one static priority list for all time steps, I do not add the heat storages as this would add significantly more complexity to the deduction process. The results from my deduced optimal control strategies for this reason not perfectly usable under real conditions for the heat storages. Secondly, assigning a priority number to *difficult-to-assign* cases comes with an uncertainty. Additionally, I can only assign a particular condition to one class whereas in reality there might be a more complex situation that leads to the condition in terms of capacity shares in a certain time step. So assigning these cases comes with both, an uncertainty of assigning it correctly and a possible complexity reduction which may lead to worse results for the deduced optimal control strategies in comparison with the optimised operation. These two aspects can be improved in future work. The method of validation of my deduced optimal control strategies is topic of the section 3.3.

Having assigned priority numbers and thereby classes to all time steps for the results from the model operation, I still need to find a way to classify my time steps under real conditions. Like this, I obtain deduced optimal control strategies that are based on my optimised operation. I classify by steering parameters. How do I identify my steering parameters and how do I classify my time steps? I want to answer this questions in the next subsection.

3.2.2 Classification via Linear Discriminant Function Analysis

For classification I use steering parameters and linear discriminant function analysis based on the toolkit from *Scikit-learn* ([28]) with the solver "*eigen*" [22]. In this subsec-

tion, I want to explain why I choose linear discriminant function analysis, how I choose my steering parameters and how the method works.

In [21, pp. 231–244], parametric, heuristic and parametric involving classification and regression trees are introduced as methodological options for classification. Looking for a method, I want a method that in the best case is already implemented in Python, is open-source as the rest of the software I use and can be reused for different use-cases - my scenarios and different KPI-options.

With the toolkit for linear discriminant analysis ([29]) from *Scikit-learn*, I have a tool that fulfills all these requirements. It is part of the parametric classification methods and "is optimal when the [...] classes are normally distributed" but is also "said to give satisfactory results" when the classes are not normally distributed. [21, p. 236] In an example given, linear discriminant function analysis is shown to be more suitable for classification than the ordinary least squares regression method. [21, pp. 236–238]

Potential Steering Parameters					
Time	Demands (3)	Costs (9)	Irradiances (2)	Temperature (1)	pv (1)
step 1 step 2 ... step n					

Table 3.5: overview of potential steering parameters in fossil-based scenario

In my concrete case, I decide to use the demands for electricity, heating and warm water, the costs, the direct and the indirect irradiance, the ambient temperature and the energy provided by the pv plant as potential steering parameters as all of these provide, in some cases, time-dependant data (see Table 3.5). I reduce the potential steering parameters to the actual steering parameters. I do so by deleting all steering parameters that do not change over time. One example for this are the costs for the emissions-optimised fossil-based scenario for the gas from the grid.

The linear discriminant analysis is then performed for a training data set that is created based on another tool [30] of *Scikit-learn*. The training data is used to deduce the function based on linear discriminant analysis. This function is then used to predict the classes for both, the test data and the whole data set consisting of both, test and train data. The test data prediction is used to validate the function that I obtain with linear discriminant analysis (see section 3.3). The prediction result for the whole data set with both, test and train data, is used to estimate the consequences for the KPI (see section 3.3).

Using the training data for both, training of the algorithm and prediction of priority numbers, comes with the risk of over-estimating my classification strategy. I nonetheless

do so and also want to give arguments for this. I only have one year of data available for training, testing and prediction. I want to predict the full year in order to compare the results nicely to the results from optimised operation. Using only some randomly chosen test data points is not possible, as I need a full time series in order to model for example the state of charge of the heat storage. Using only the last month for prediction might mislead as there is a seasonal difference in the data. Additionally, I use linear discriminant analysis which in my case has no endless degrees of freedom. This means that my classification function does not yield perfect prediction for the training data set. Instead, the rate of correct predictions is very similar for both, the test and the train data set. Therefore, I think that it is valid to use the full year of data for prediction and validate my deduced optimal control strategies with it.

Resulting Priority Lists for Validation Based on...		
Time	... Class Definition	... Classification
step 1 step 2 ... step n		

Table 3.6: resulting priority lists for validation

So, for validation, there now exist two priority list time series for the whole time frame based on the class definitions from section 3.1 and the function from this section used for classification (see Table 3.6).

The mathematical formulation of the linear discriminant analysis and the way of classifying new data through prediction in *Scikit-learn* can be found in [22].

As a critical comment, I want to mention that I only considered classification methods mentioned in [21, pp. 231–252]. Additionally, I decide for linear discriminant function analysis not based on a profound analysis of its performance in comparison to the other options provided, but based on availability as already-implemented python libraries. Other methods like heuristic or parametric involving classification and regression trees can be better options which are not analysed in this thesis.

3.2.3 Expected Results for Deduced Optimal Control Strategies

For the deduced optimal control strategies, I expect to obtain a function with weights for the steering parameters, a share of correctly predicted classes for the test data set, a share of correctly predicted classes for the whole data set, a time series of the priority lists as they are defined based on subsection 3.2.1 and a time series of the priority lists as they are predicted by the function based on the linear discriminant function analysis.

I only deduce optimal control strategies for the fossil-based scenario.

3.3 Validate Optimal Control Strategies

Equipped with the two sets of priority lists from section 3.2, I now describe how I validate the optimal control strategies.

3.3.1 Implementing Optimal Control Strategies in oemof

For my validation, I use the same oemof-model as for optimising operation (3.1). The priority lists for the fossil-based scenario are electricity- and heat-specific as well as KPI-specific.

One priority list with KPI-specific Priority Numbers					
Time	pv (el)	chp (el)	grid (el)	chp (th)	boiler (th)
step 1	1	2	3	1	2
step 2	1	2	3	1	2
...	...	...	...	...	...
step n	1	2	3	1	2

Table 3.7: one priority list with KPI-specific priority numbers for validation (*el*: electricity output, *th*: heat output)

A possible outcome could look like Table 3.7. The values in the table are example values that I use to explain the method and are no actual results.

One priority list with KPI-specific Costs					
Time	pv (el)	chp (el)	grid (el)	chp (th)	boiler (th)
step 1	10	100	1000	10	100
step 2	10	100	1000	10	100
...	...	...	...	...	...
step n	10	100	1000	10	100

Table 3.8: one priority list with KPI-specific costs for validation (*el*: electricity output, *th*: heat output)

The values from Table 3.7 are then transformed to costs that I can use in my oemof-model to make sure that the priority order is kept from the priority number to ten to the power of the priority number. The result is shown in Table 3.8.

These costs are then used to solve the model in oemof. The costs for electricity are the same as the costs *1*, *5* and *9* in Figure 3.6. The costs for heat are added in the same manner at the heat output of the gas-powered chp and boiler. The resulting values for the KPI are then compared to the values from the optimised operation.

Commenting critically on the method, there are some things to highlight. First of all, the heat storages are not steered by priority numbers but are still optimised by the model and therefore better as the realistic result. Using the same model nonetheless has the advantage, that I have exactly the same equations and components as in the optimisation of the operation and the time-effort of reusing the model is significantly lower than the one of reimplementing the equations and components as python code.

Additionally, the deduced priority lists with the classification method include the data of the training data set. I argued for this choice and why it is valid in the previous section. Nonetheless, it might be an additional source of error.

3.3.2 Expected Results for Optimised Control

For the validation, I expect results only for the fossil-based scenario as I only deduce optimal control strategies for this scenario. I want to obtain KPI-results for both priority lists from the class definition before the linear discriminant analysis and from the classification based on the function resulting from the linear discriminant analysis. This means six KPI-values for each KPI. I want to compare these KPI-values to the ones that I obtained from optimised operation. From these values, I want to interpret whether my approach of priority lists as classes can yield good results and whether my classification strategy based on the approach of priority lists can yield good results.

4 Data

In this chapter, I want to give an overview about the concrete data that I use for my optimisation of operation which is the foundation for the following deduction of optimal control strategies. In *4.1*, I explain the framework of both scenarios like for example the size of the modelled district, the time frame and the demands. After setting the frame, I explain the scenario-specific parameters of each installed technology in *4.2*. Finally, I introduce the scenario- and KPI-specific costs for both scenarios in *4.3*. A detailed description of all referenced data and equations used, including the oemof-optimisations, is available in my git-repository which is DLR-VE-internally accessible.

4.1 Framework for Both Scenarios

In this section, I present the data framework of both scenarios.

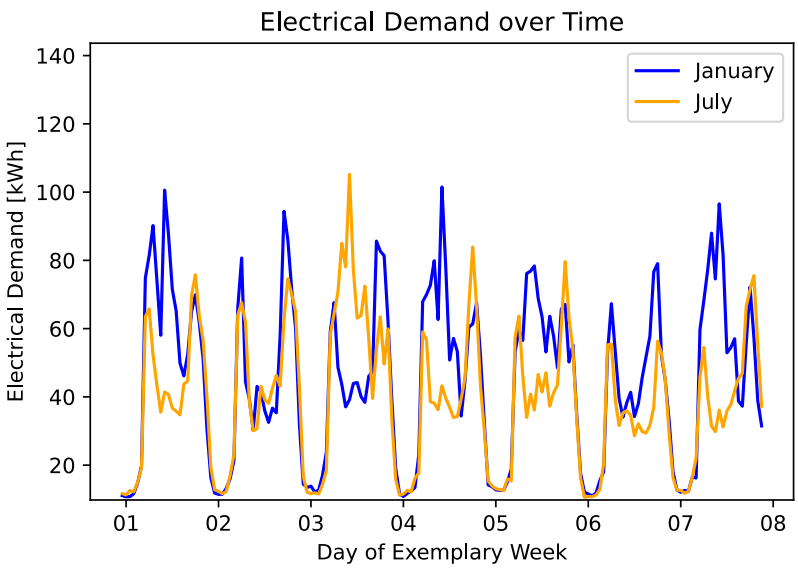

Figure 4.1: hour-specific electricity demand over time for two exemplary weeks of the year

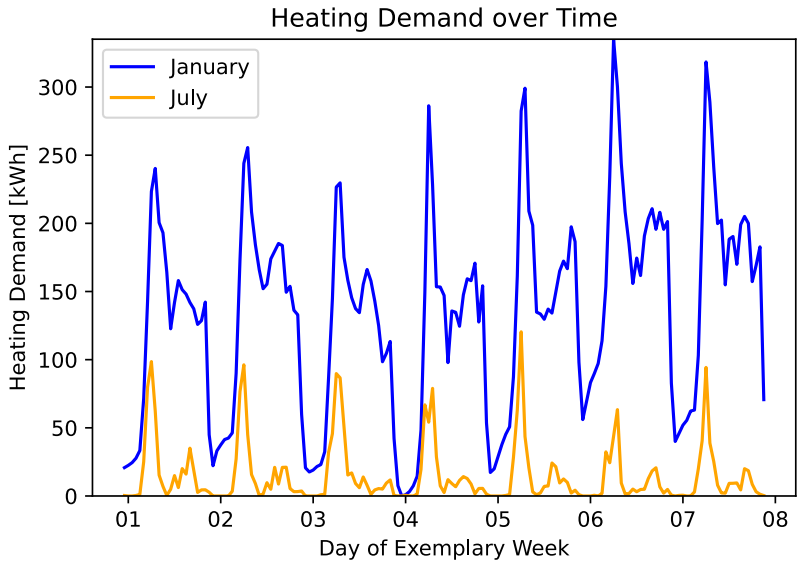

Figure 4.2: hour-specific heating demand over time for two exemplary weeks of the year

The modelled energy system shall be comparable to the ENaQ-project. In the ENaQ-project, approximately 140 households are expected to live. For this district, I want to optimise the operation for 1 year of input data. The modelled step size within this time frame shall be 1 hour.

Yearly Demands for Both Scenarios		
Dimension	Unit	Value
electricity	MWh	376.361
heat for heating	MWh	401.517
heat for warm water	MWh	336.203

Table 4.1: yearly demands for both scenarios

In Table 4.1, the accumulated demands for electricity and heat for both, heating and warm water, are shown. The data for the demands are provided by the ENaQ-project at DLR-VE as time series data with a resolution of at least 1 h.

In Figure 4.1, I show the electrical demand for two exemplary weeks in January and July. Similarly, the demands for heating (Figure 4.2) and warm water (Figure 4.3) are shown. For all figures, the limits of the vertical axis are the minimum and maximum values of the time series. The idea is to give an insight in the non-intuitive time series data I use.

The electrical demand does vary strongly within the day but only slightly throughout

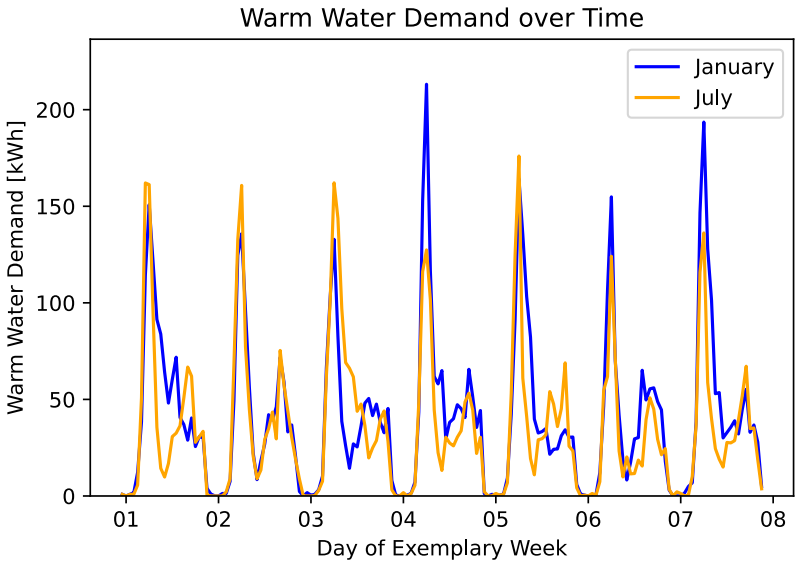

Figure 4.3: hour-specific warm water demand over time for two exemplary weeks of the year

the year. The peak value does not exceed 150 kWh within 1 h.

In contrast, the heating demand varies strongly over the year as well as over the day. The peak value exceeds 300 kWh within 1 h in winter but does not exceed 150 kWh in summer weeks.

The warm water demand, comparable to the electricity demand, does not vary much over the year. Within a day it varies a lot with a peak in the morning hours.

For my models, I use technical and time series data from 2017. Nonetheless, I try to use up-to-date data on the subsidies and legal conditions when they are available. For all optimisations I only consider such costs that are part of the operation. I do not consider investment costs in terms of prices or emissions from production. The resulting KPI-specific values for the costs are presented in section *4.3*. Before jumping there, I want to introduce the scenario-specific parameters of all technologies in the next section.

4.2 Parameters of Installed Technologies

In this section, I want to give an overview of the most important parameters of all technologies used in both scenarios.

4.2.1 Fossil-Based Scenario

In the fossil-based scenario, I implement the technologies pv, gas-powered chp, gas-powered boiler and a heat storage.

Photovoltaic Power Plant (Fossil-Based Scenario)		
Dimension	Unit	Value
installed capacity	kW	100

Table 4.2: parameters of photovoltaic power plant in fossil-based scenario

Gas-Powered Combined Heat and Power Plant		
Dimension	Unit	Value
upper heating value	kW	143
upper maximum thermal power output	kW	85
upper maximum electrical power output	kW	50
lower heating value	kW	89
lower maximum thermal power output	kW	53
lower maximum electrical power output	kW	25

Table 4.3: parameters of gas-powered combined heat and power plant

Gas-Powered Boiler		
Dimension	Unit	Value
efficiency	%	90

Table 4.4: parameters of gas-powered boiler

The energy feed-in of pv is based on the installed capacity shown in 4.2. This capacity is then combined with a time series on a local pv installation in order to calculate the hour-specific energy-supply through pv. The time series is provided by the ENaQ-project at DLR-VE.

The installed capacity is chosen to be smaller than the one in the renewable-based scenario, specifically two thirds of the one in the renewable-based scenario. This is done in line with the description of this scenario as the fossil-based and therefore equipped with less renewable resources. Installing some pv shall make it possible to show the effects of a pv-installation in a fossil-based energy system.

For both, gas-powered chp and boiler, the imported gas is reduced by the factor between the upper and the lower heating value. According to DIN V18599 which is used in the ENaQ-project at DLR-VE as well, the factor between lower and upper heating value is *1.11*.

The parameters of the chp (table 4.3) and boiler (table 4.4) are taken from already

existing models at the ENaQ-project at DLR-VE. The gas-powered boiler is not capacity-limited in the model. This means that it can provide all the energy that is required in order to meet the demand. As sizing and design is not part of this thesis and meeting demand is not optional but required, this is a justifiable simplification.

Heat Storage (Fossil-Based Scenario)		
Dimension	Unit	Value
height	m	7
volume	m^3	50
insulation width	m	0.10
insulation conductance	$W\,m^{-1}\,K^{-1}$	0.04
lower temperature limit	°C	15
upper temperature limit	°C	45

Table 4.5: parameters of heat storage in fossil-based scenario

The lower and the upper limit of the temperature of the heat storage (Table 4.5) are based on the inner building and the warm water temperature. The other parameters for the heat storage are based on data from the ENaQ-project at DLR-VE.

4.2.2 Renewable-Based Scenario

In the renewable-based scenario, I implement the technologies pv, a solar thermal power plant, a heat pump, an electric boiler, a warm and a cold heat storage.

Photovoltaic Power Plant (Renewable-Based Scenario)		
Dimension	Unit	Value
installed capacity	kW	150

Table 4.6: parameters of photovoltaic power plant in renewable-based scenario

The energy feed-in of pv is based on the installed capacity shown in Table 4.6. This capacity is then combined with a time series on a local pv installation provided by DLR-VE in order to calculate the hour-specific energy-supply through pv.

In the renewable-based-scenario, the size of the pv-installation is defined based on the available horizontal roof-top area in the district of ENaQ. The idea is to use around half of the available area for pv and the other half for solar thermal. The available horizontal roof-top area is $3\,067.85\,m^2$. I assume 70 % of this area to be usable as aperture area. With the help of an exemplary data sheet from EWE, a local supply company, for a pv-module ([31]) and its data on the power of a module, its height and length, I calculate the installed capacity that this area allows. This installed capacity is shown in Table 4.6.

Solar Thermal Power Plant		
Dimension	Unit	Value
collector tilt	°	10
collector azimuth	°	20
optical efficiency	%	73
aperture area	m^2	1050.33
low inlet temperature	°C	5
medium and high inlet temperature	°C	15
low outlet temperature	°C	15
medium outlet temperature	°C	30
high outlet temperature	°C	45

Table 4.7: parameters of solar thermal power plant

The parameters of the solar thermal power plant are shown in Table 4.7. The collector tilt and azimuth and the optical efficiency are taken from the ENaQ-project at DLR-VE. The aperture area is calculated based on the available horizontal roof-top area as for the pv installation. The inlet and outlet temperatures for the operational temperatures medium and high are based on the warm water (45 °C) and heating (30 °C) temperature, the ambient temperature of the warm heat storage which is placed inside the houses (15 °C) and the cold heat storage which is based outside the building (5 °C). The outlet in the operational state with a low temperature is chosen to be at the upper limit of the cold heat storage.

Heat Pump		
Dimension	Unit	Value
maximum thermal power output	kW	283

Table 4.8: parameters of heat pump

Electric Boiler		
Dimension	Unit	Value
efficiency	%	95

Table 4.9: parameters of electric boiler

The maximum thermal power output of the heat pump (Table 4.8) is based on data from the ENaQ-project at DLR-VE and the data sheet of the *Vitocal 300-G Pro* ([32, p. 18]). The efficiency of the electric boiler (table 4.9) is based on data from the ENaQ-project at DLR-VE.

For the warm (Table 4.10) and cold (Table 4.11) heat storages, the height, volume, insulation width and insulation conductance are chose as in the heat storage of the fossil-based scenario (4.2.1). The warm heat storage's three temperature limits are chosen based on

Warm Heat Storage (Renewable-Based Scenario)		
Dimension	Unit	Value
height	m	7
volume	m^3	50
insulation width	m	0.10
insulation conductance	$W\,m^{-1}\,K^{-1}$	0.04
lower temperature limit	°C	15
medium temperature limit	°C	30
upper temperature limit	°C	45

Table 4.10: parameters of warm heat storage in renewable-based scenario

Cold Heat Storage (Renewable-Based Scenario)		
Dimension	Unit	Value
height	m	7
volume	m^3	50
insulation width	m	0.10
insulation conductance	$W\,m^{-1}\,K^{-1}$	0.04
lower temperature limit	°C	5
upper temperature limit	°C	15

Table 4.11: parameters of cold heat storage in renewable-based scenario

the inner building, the heating and the warm water temperature. The two temperature limits of the cold storage are chosen based on the ambient temperature outside of the building (under ground) and a reasonable value between the heating temperature and this ambient temperature. Reasonable in this case refers to a temperature that allows much operational time of the solar thermal power plant in this state while at the same time maintaining a not-too-big temperature difference that the heat pump has to cover to the heating and to the warm water temperature level.

Having defined the framework and the technologies, I now want to explain the costs with which the optimisation via oemof is implemented.

4.3 Costs in Optimisation

The optimisation in oemof is done with costs as explained in subsection 3.1.5. In this section, I want to present the data for the scenario-specific costs.

4.3.1 Fossil-Based Scenario

In Figure 3.6 (subsection 3.1.5), I explained the point of costs for the fossil-based scenario. All costs are energy-specific. As I work with *MWh* as unit for energy, my costs are *MWh*-specific.

Energy-specific Costs (Fossil-Based Scenario)			
no.	Emissions [t/MWh]	Exergy [MWh/MWh]	Prices [EUR/MWh]
1	0.167...0.797	1.224...1.704	34.07...280.65
2	0	0	-249.84
3	0	0	-50.00
4	0	0	-72.90
5	0	1.000	67.56
6	0.201	1.100	42.57
7	0	0	-5.50
8	0	0	-243.52...3.06
9	0	0	27.56

Table 4.12: data for costs in model-optimisation of fossil-based scenario

In Table 4.12, the costs at the nine points of costs for the fossil-based scenario are presented. The costs are KPI-specific for emissions, exergy and prices.

The emissions of electricity from the grid are based on [33]. There, the emissions from electricity in the grid are calculated as an hour-specific average and dependant on the power plants operating in a particular region within the European transmission grid. The values in the table are the minimum and the maximum value for my reference year (2017). The emissions for natural gas are from a report of 2016 [34, p. 47] of the "*Umweltbundesamt*" for Germany in 2014.

I assume the local electricity from pv to be pure exergy which leads to the exergy-costs shown in Table 4.12. For the exergy of gas from the gas grid, I use a constant value from [35, p. 6]. The exergy of the electricity of the grid is calculated as consistent with the emissions as possible. I use data of the entso-e [36] for the region *BZN - DE-AT-LU* to calculate the share of fossil and renewable energy feed-ins for each hour in 2017. In order to calculate a relative exergy-input from these shares, I use the primary energy factors of the power plants as best available guess for the relative exergy-input. For fossil-based energy, I assume 1.800 MWh/MWh according to [35, p. 6]. For renewable-based energy I set 1.050 MWh/MWh. This is not consistent in terms of using the primary energy factor. I still do so as I want to optimise for local exergy use. Locally, pv-electricity has a value of 1.000 MWh/MWh. As for an exergy-optimisation valueing grid-electricity from pv lower than local pv does not make sense, I consider a 5%-loss in the grid and the same 1.000 MWh/MWh as the local pv as the minimum value for grid electricity's

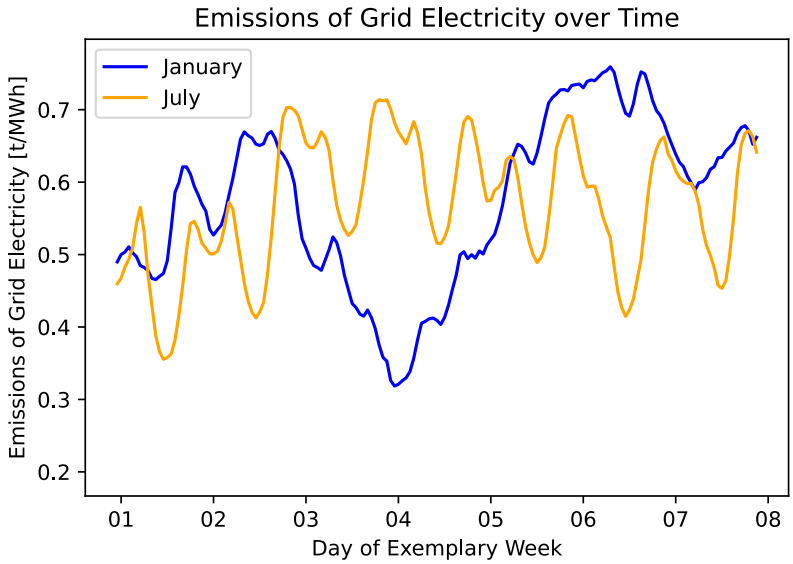

Figure 4.4: hour-specific costs for imports of electricity in terms of emissions over time for two exemplary weeks of the year

exergy. The combination of these data leads to the minimum and maximum value for the exergy of the electricity from the grid shown in Table 4.12.

To calculate the costs in terms of prices for electricity of the grid, I also create a time series with the minimum and maximum value for 2017 shown in Table 4.12. In these prices are the grid-use-levies (at *grid level 6*, 20 kV/0.4 kV, [37, p. 4]), the power prices dependant on yearly full-load-hours ([37, p. 4]), concession levies (*§2 (3) 1.* "*Sondervertragskunden Strom, Maximum*", [38]), levies for the Erneuerbare Energien Gesetz (EEG) (2020, [39]), levies for the Kraft-Wärme-Kopplungs-Gesetz (KWKG) (2020, [40]), levies for Abschaltbare-Lasten-Verordnung (AbLaV) (2020, [41]), offshore-levies (2020, [42]), the electricity tax (2020, "*Stromsteuer*", [43]) and day-ahead prices (2017, region *DE-AT-LU*, [44]) included.

The revenues for the supply with electricity are calculated as 90 % of a local tariff ("*Grundversorgungstarif*", 4 500 kWh/year, [45]). The heating revenue is a value from the ENaQ-project at DLR-VE. The revenue for exports of electricity from pv is based on ("*Anzulegende Werte für Solaranlagen Mai bis Juli 2020*", size within the range of 40 kW and 750 kW, "*Anzulegende Werte in Cent/kWh - Marktprämienmodell*" for residential buildings, [46]). As for local electricity from pv there is a need to pay the EEG-levies as well, the EEG-levies are the price for local electricity from pv.

In the imports from the gas grid the demand-dependant grid charge ("*Netzentgelte Gas*

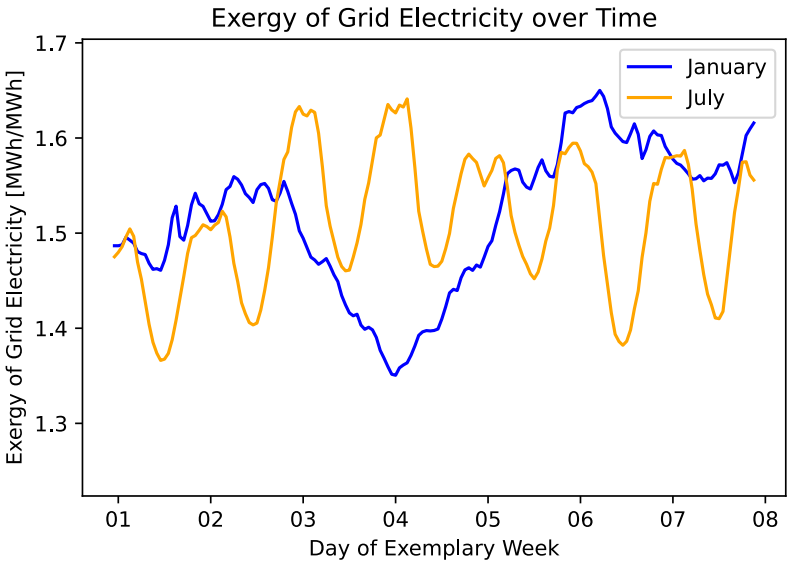

Figure 4.5: hour-specific costs for imports of electricity in terms of relative exergy-input over time for two exemplary weeks of the year

2020 - Örtliches Verteilernetz", [47, p. 6]), the energy tax ([48]), the concession levies ("*Netzentgelte Gas 2020 - Örtliches Verteilernetz*", [47, p. 10]) and a working price ("*Netzentgelte Gas 2020 - Örtliches Verteilernetz*", *zone 3*, [47, p. 4]) are included.

For gas that is used in the chp, there is no need to pay the gas-tax which I model in form of a revenue for this energy flow. The costs for the electricity of the gas-powered chp that is exported are the sum of the day-ahead-prices that I also use to calculate the prices for imports of grid electricity and the subsidies for export of electricity from the gas-powered chp ("*Strom für Kund[*inn]enanlagen*", electrical power below 50 kW, [49]). The costs for the local use of electricity from the gas-powered chp are the sum of the EEG-levies and the subsidied for the local use of the electricity form the gas-powered chp ("*ausgespeister Strom*", electrical power below 50 kW, [49]).

In Figure 4.4, I show the hour-specific costs for electricity imports from the grid in terms of emissions for two exemplary weeks in January and July. Similarly, the hour-specific costs for electricity imports from the grid in terms of relative exergy-input (Figure 4.5) and prices (Figure 4.6) are shown. For all figures, the limits of the vertical axis are the minimum and maximum values of the time series. These time series plots shall give an insight in the variations over time that are more deep than the minimum and maximum values shown in Table 4.12. The costs for electricity imports are the same for both scenarios.

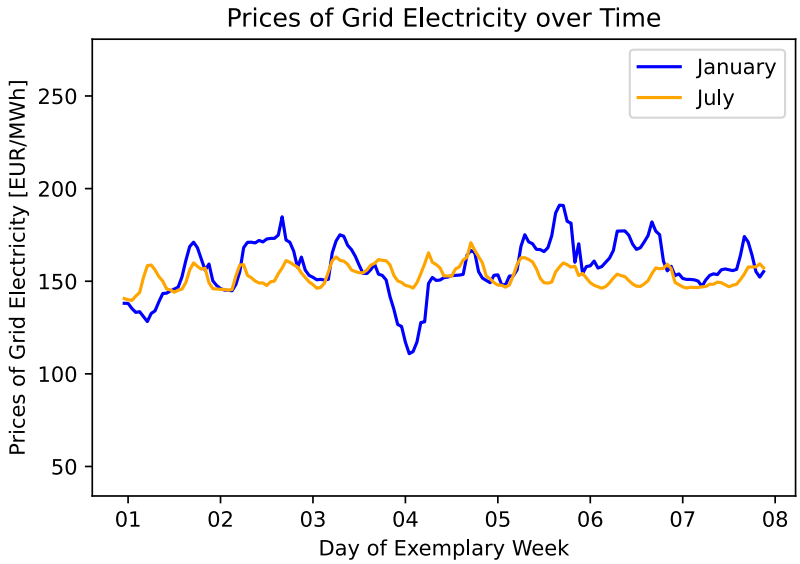

Figure 4.6: hour-specific costs for imports of electricity in terms of prices over time for two exemplary weeks of the year

The costs in terms of emissions do vary throughout the year. There is a seasonal variance due to more irradiance in the summer and more wind in winter. There is a within-day variance due to the highest irradiance in the middle of the day. Similarly, the relative exergy-input of the imports of electricity from the grid varies over time.

The costs in terms of prices vary significantly less with a lot higher peaks compared to the costs in terms of emissions and relative exergy-input for the imports of electricity from the grid. As the vertical axis limits are the minimum and maximum values of the time series shown in Figure 4.4 to 4.6, this can directly be derived from the smaller vertical spread over the plot in Figure 4.6.

Having introduced the data for the fossil-based scenario: What are the differences in terms of data in the renewable-based scenario?

4.3.2 Renewable-Based Scenario

In Figure 3.7 (subsection 3.1.5), I explained the points of costs for the renewable-based scenario.

In Table 4.13, the costs for the renewable-based scenario are shown. The costs *1 to 5* are the same as in the fossil-based scenario.

Energy-specific Costs (Renewable-Based Scenario)			
no.	Emissions [t/MWh]	Exergy [MWh/MWh]	Prices [EUR/MWh]
1	0.167...0.797	1.224...1.704	34.07...280.65
2	0	0	-249.84
3	0	0	-50.00
4	0	0	-72.90
5	0	1.000	67.56
6	0	-0.052...0.080	0
7	0	0.000...0.126	0
8	0	0.047...0.167	0

Table 4.13: data for costs in model-optimisation of renewable-based scenario

The costs for the heat of the solar thermal power plant (*6 to 8*) are *0* for the emissions- and the price-optimised renewable-based scenario.

For the exergy-optimised case, the costs for the heat of the solar thermal power plant depend on its operational state, specifically on its output temperature. The exergy costs are determined as a function of the ambient temperature and the output temperature of the solar thermal power plant. The costs can become negative if the ambient temperature is bigger than the output temperature. Important for the optimisation is here that low temperature solar thermal power is preferred over high temperature solar thermal power. Lower temperatures lead to lower losses in the district's heat network due to lower temperature differences in the grid and more possible time of operation for the solar thermal power plant for a period of 1 year.

After presenting the theory I build upon, my methodology and the data I used, I now want to present and discuss my results.

5 Results and Discussion

I present and discuss my results in line with the structure of my research questions through guiding sub-questions. I start with the results on optimal operation (5.1) answering my first sub-question, continue with the deduced optimal control strategies (5.2) answering my third sub-question and the first part of my research question and finish with the results on validation of the deduced optimal control strategies (5.3) in order to answer my fourth sub-question and the second part of my research question.

5.1 Optimal Operation

In this section, I present and analyse the results on optimal operation. I have a look on the results for each KPI step by step for both scenarios with the three different optimisation goals each at the same time. I thereby answer my first guiding sub-question "*Which optimal operations can be derived with the existing model from the chosen KPI for optimisation and what are the resulting greenhouse gas emissions for each optimisation?*". As I already highlighted the importance of the emissions in this sub-question, I start with the results for the emissions.

In Figure 5.1, I present the results of the optimised operation in terms of demand-specific emissions. For each scenario, there are the resulting emissions for the optimised operation (in the figure: "*opt_ope*") on all the three KPI: emissions, exergy and prices.

As expected, for emissions the emission-optimised operation has the lowest values with 0.237 t/MWh for the fossil-based scenario and 0.285 t/MWh for the renewable-based scenario. In the fossil-based scenario, the exergy-optimisation leads to 1.6 % and the price-optimisation to 12.0 % more emissions than the emission-optimised operation. In the renewable-based scenario, the exergy-optimisation leads to 1.4 % and the price-optimisation to 2.1 % more emissions than the emission-optimised operation.

Other than expected, the emissions in the renewable-based scenario optimised for emissions are 20.0 % higher in the renewable-based scenario than in the fossil-based scenario - other than the name would suggest.

This leads to two conclusions: Firstly, the design of the energy system of the fossil-based

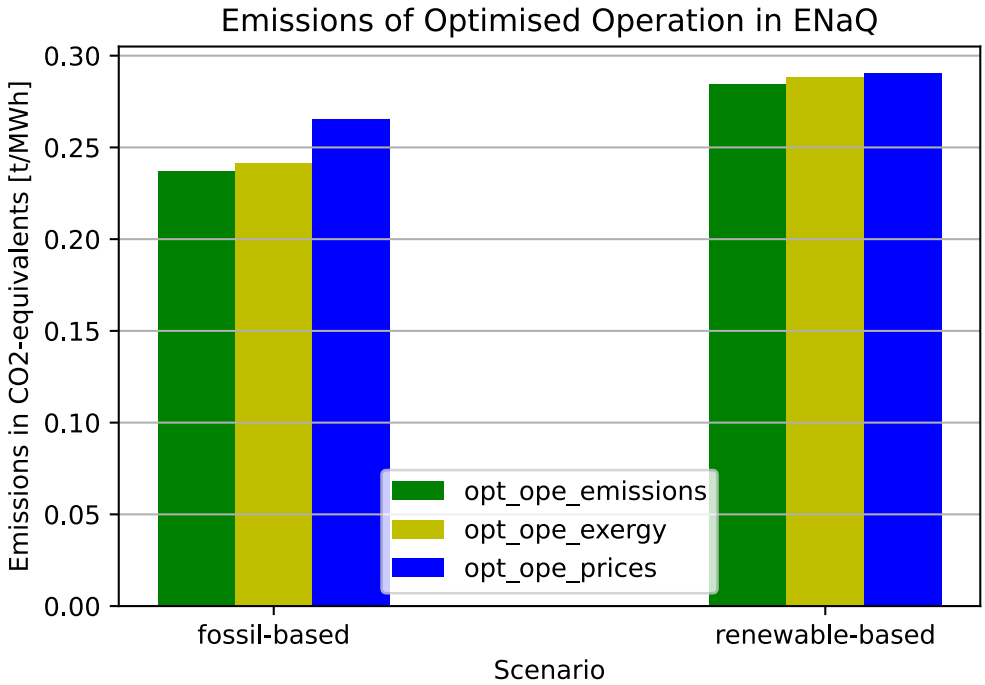

Figure 5.1: results in terms of emissions for optimised operations - both scenarios (*opt_ope*: optimised operation for)

scenario leads to lower emissions for the data from the reference year in 2017 than the design of the renewable-based scenario. Secondly, for the fossil-based scenario exists a significant potential for improvement when optimising the operation for emissions and not for prices - the emissions are 12.0 % higher if not optimised for emissions.

But why is that so? In the following I answer some questions that emerge from the results:

- Why are the emissions in the renewable-based scenario higher than in the fossil-based scenario?
- Why does the optimisation on exergy lead to higher emissions - although the difference is small?
- Why are the emissions in the price-optimised fossil-based scenario higher than in the emissions- and exergy-optimised cases?

In order to better understand the source of emissions of the renewable-based scenario, I

want to have a look on the shares in the energy supply of each technology for electricity (Figure 5.4) and heat for both, heating (Figure 5.2) and warm water (Figure 5.3).

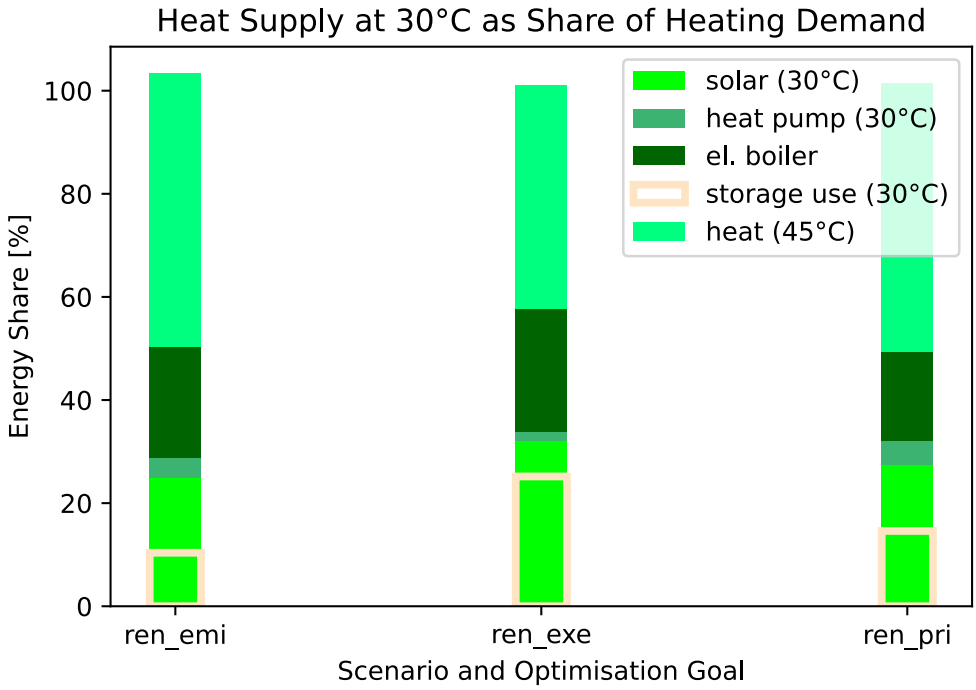

Figure 5.2: heat supply at 30 °C as share of heating demand - renewable-based scenario (*ren*: renewable-based scenario, *emi*: optimised on emissions, *exe*: optimised on relative exergy-input, *pri*: optimised on prices)

In Figure 5.2, the shares each technology of the total supply of heat at 30 °C over the full year are shown. The values are shares of the heating demand and can therefore grow bigger than 100 % as part of the heat at 30 °C may be used to supply a part of the heat at 45 °C. The *storage use (*30 °C*)* is the total heat that the storage fed back to the heat supply bus at 30 °C and is therefore not added cumulatively as the other bars but shown as a share of the total heat demand. *heat (*45 °C*)* is heat at 30 °C that is supplied by heat generated at 45 °C and then transformed to heat at 30 °C.

With regard to the higher emissions for the exergy-optimisation than for the emissions-optimisation, at notifyable difference is that the share of heat at 45 °C increases from the exergy-optimisation with 43.3 % to 53.1 % for the emissions-optimised scenario. Also, the share of the heat pump increases from 1.7 % to 3.9 % in the emissions-optimised scenario. The share of solar thermal heat decreases from 32.1 % to 24.9 %. It seems that from an exergy-perspective solar heat at 30 °C is preferred whereas from an emissions-perspective the heat pump and heat at 45 °C is preferred. Although the exergy-optimisation only

leads to an increase in overall emissions of 1.6 % and therefore quite small.

As one can see, more than 10 % of the heating demand are supplied by the electric boiler and therefore electricity. Also, a share of around 45 % is supplied by heat that is generated at 45 °C. So how is the heat at 45 °C supplied?

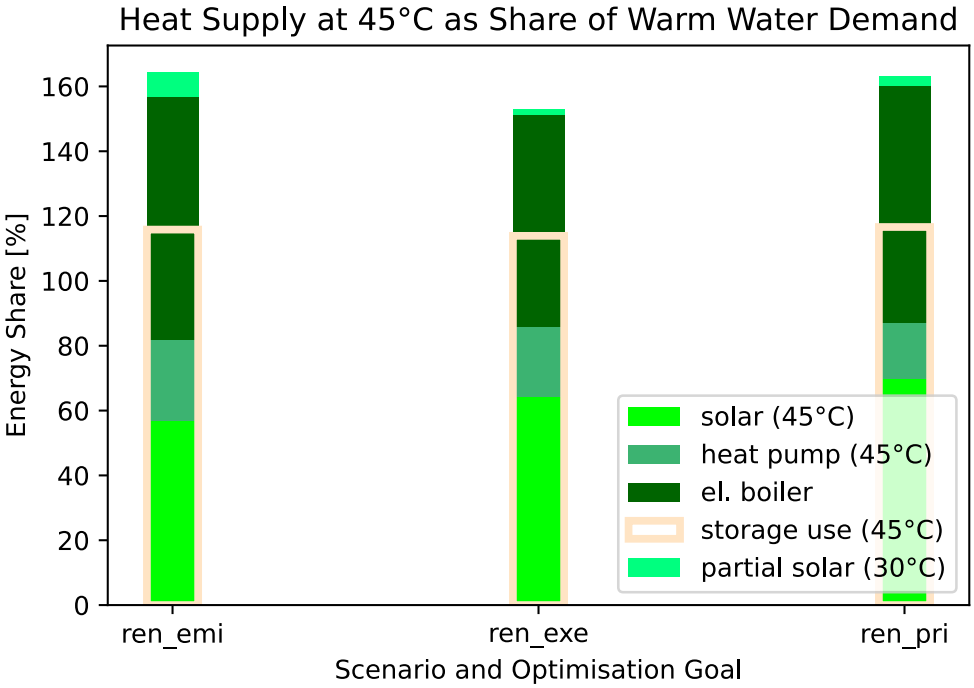

Figure 5.3: heat supply at 45 °C as share of warm water demand - renewable-based scenario (*ren*: renewable-based scenario, *emi*: optimised on emissions, *exe*: optimised on relative exergy-input, *pri*: optimised on prices)

In Figure 5.3, the energy shares over the full year of all technologies for the supply of heat at 45 °C are shown for the renewable-based scenario. The values again are relative to the demand for warm water and can therefore be bigger than 100 %. As we have seen in Figure 5.2, the shares actually need to be bigger than 100 % as a huge part of the heat at 30 °C is supplied by heat that is generated at 45 °C. The *partial solar (*30 °C*)* share is the share of heat at 45 °C that is supplied partly by heat at 30 °C and partly by heat from the electric boiler.

With regard to the higher emissions for the exergy-optimisation than for the emissions-optimisation, again the share of the heat pump is with 25.1 % to 21.5 % higher for the emissions-optimisation. The share of heat from the solar thermal power plant at 45 °C is with 64.4 % compared to 56.8 % higher for the exergy-optimisation.

Having a look on the origin of the higher emissions in the renewable-based scenario than in the fossil-based scenario, again from 65.2 % up to 74.9 % are supplied by the electric boiler and therefore electricity. None of the other technologies is a direct source of emissions. Therefore, the source of emissions in the renewable-based scenario lies in the big amount of electricity used for the supply of heat.

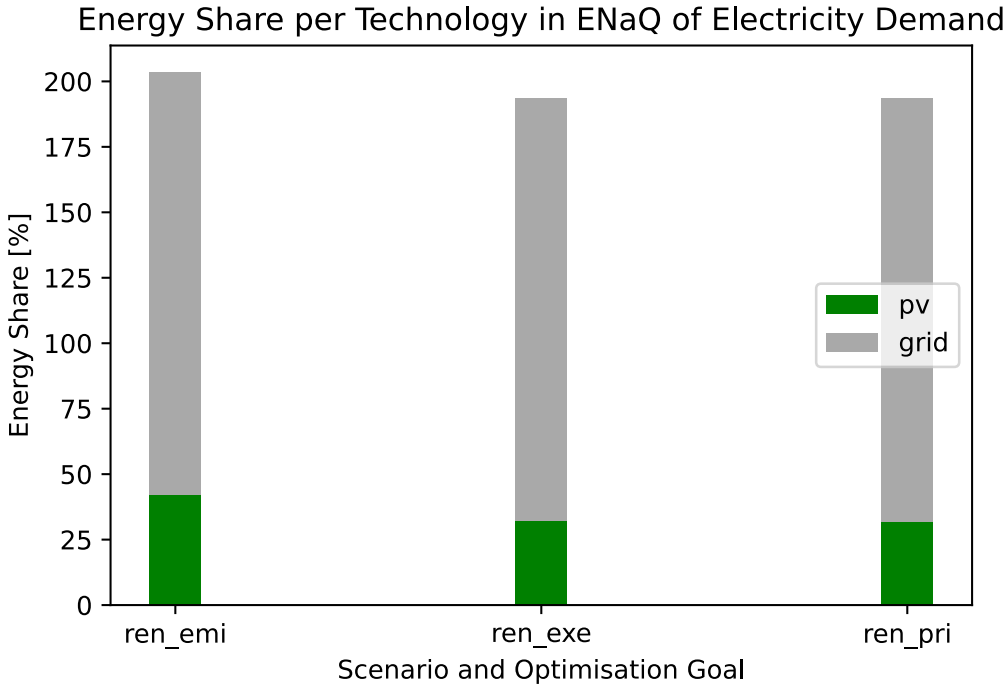

Figure 5.4: technology-specific energy shares for electricity as accumulated sum of energy supply flows over the year over demand - renewable-based scenario (*ren*: renewable-based scenario, *emi*: optimised on emissions, *exe*: optimised on relative exergy-input, *pri*: optimised on prices)

In Figure 5.4, the shares on the energy supply of electricity for the renewable-based scenarios are shown. As expected from Figure 5.2 and Figure 5.3, the shares of the supply of electricity are far bigger than 100 % and to a huge extend supplied by electricity from the grid. This is the reason for the renewable-based scenario having worse results than the fossil-based scenario: The grid emissions in 2017 were very high. I want to highlight that this situation might significantly change over the next years with the ongoing energy transition. On the other hand, the emissions of the gas from the local chp in the fossil-based scenario stay constant.

Whereas the shares for the grid electricity remain almost constant for all optimisations between 161.4 % and 161.9 %, the shares of pv differ from 31.7 % in the price-optimisation

over 32.1 % in the exergy-optimisation up to 42.1 % in the emissions-optimisation. And this is the reason for the emissions-optimisation to have less emissions than the exergy-optimisation. For the emissions-optimisation, electricity from pv does not produce any emissions and can therefore be used for the supply of the electricity of the heat pump. For the exergy-optimisation instead, the electricity from pv produces costs that, depending on the supplying power plants in the grid, might only be a little bit lower than the costs for electricity from the grid. In these cases for the exergy-optmisation, the solar thermal power plant supplies at 30 °C or 45 °C instead of 15 °C and the rest that can not be supplied is supplied by the electric boiler. The emissions-optimisation leads to the solar thermal power plant operating with an output temperature of 15 °C and the use of the heat pump. This is the reason for the small difference in the emissions for the emissions- and exergy-optimisations.

Now, I want to have a look on the higher emissions in the price-optimised fossil-based scenario.

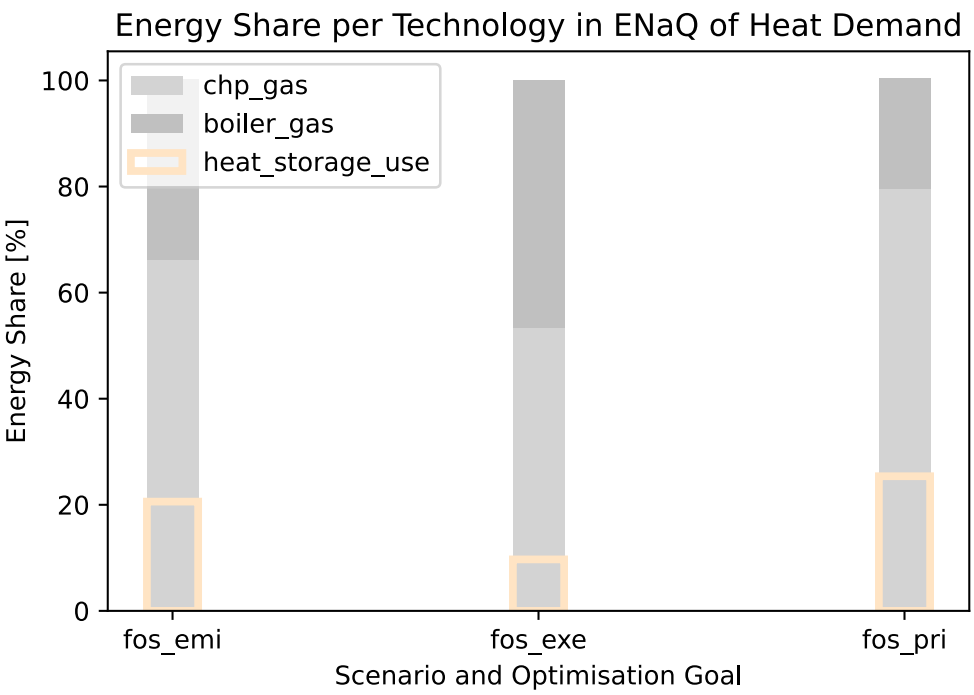

Figure 5.5: technology-specific energy shares for heat as accumulated sum of energy supply flows over the year over demand - fossil-based scenario (*fos*: fossil-based scenario, *emi*: optimised on emissions, *exe*: optimised on relative exergy-input, *pri*: optimised on prices)

In Figure 5.5, the energy shares of the technologies for the heat supply for both, heating

and warm water, for the fossil-based scenario are shown.

The share of heat from the gas-powered chp plant differs from 53.4 % in the exergy-optimisation up to 79.6 % in the price-optimisation. Respectively the share in the supply of the gas-powered boiler changes. This indicates a higher preference of the gas-powered chp in the price-optimisation compared to the other two optimisations.

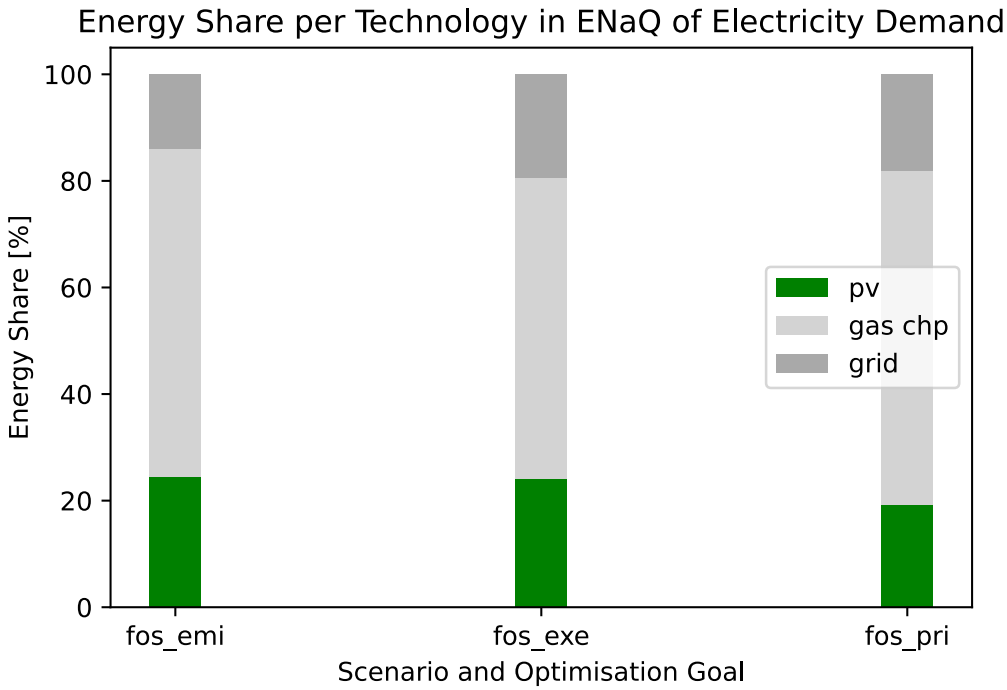

Figure 5.6: technology-specific energy shares for electricity as accumulated sum of energy supply flows over the year over demand - fossil-based scenario (*fos*: fossil-based scenario, *emi*: optimised on emissions, *exe*: optimised on relative exergy-input, *pri*: optimised on prices)

In Figure 5.6, the energy shares of the technologies for the electricity supply for the fossil-based scenario are shown.

In the price-optimisation, the share of electricity from pv is with 19.2 % compared to 24.6 % in the emissions-optimisation significantly lower. At the same time, the share of chp is with 62.8 % a lot higher than in the exergy- (56.4 %) and a bit higher than in the emissions-optimisation (61.4 %). The share of the electricity from the grid is with 18.0 % higher than in the emissions- (14.1 %) and lower than in the exergy-optimisation (19.5 %). Together, the share of chp and grid is the biggest in the price-optimisation - which is the reason for the higher emissions in this optised operation.

Having analysed in detail the results in terms of emissions - what are the results in terms of exergy-input?

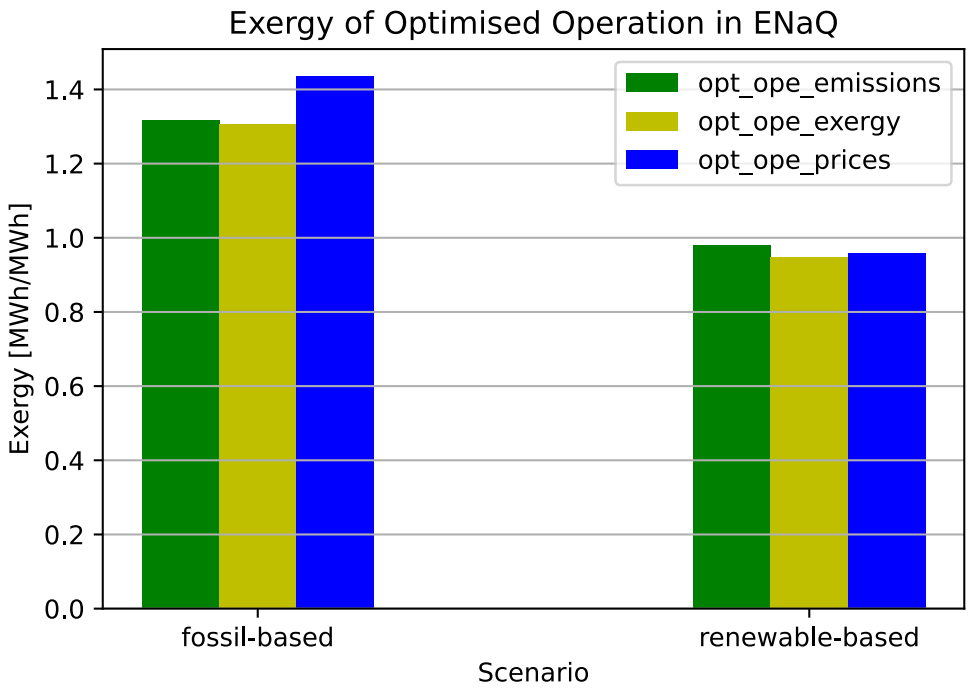

Figure 5.7: results in terms of relative exergy-input for optimised operations - both scenarios (*opt_ope*: optimised operation for)

In Figure 5.7, I present the results of the optimised operation in terms of demand-specific exergy-input. For each scenario, there is shown the resulting relative exergy-input for the optimised operation on all the three KPI: emissions, exergy and prices.

As expected, for exergy-input the exergy-optimised operation has the lowest values with 1.305 MWh/MWh for the fossil-based scenario and 0.947 MWh/MWh for the renewable-based scenario. In the fossil-based scenario, the emissions-optimisation leads to 1.0 % and the price-optimisation to 10.1 % more exergy-input than the exergy-optimised operation. In the renewable-based scenario, the emissions-optimisation leads to 3.7 % and the price-optimisation to 1.2 % more relative exergy-input than the exergy-optimised operation.

The relative exergy-input in the renewable-based scenario optimised for exergy are 27.5 % lower in the renewable-based scenario than in the fossil-based scenario.

The results in terms of relative exergy-input are lower in the renewable-based scenario than in the fossil-based scenario because the exergy input for the solar thermal power

plant is far below 1 MWh/MWh - which is the lowest possible value for the technologies of the fossil-based scenario.

In the fossil-based scenario, the exergy-results for the price-optmisation are the worst due to the higher use of electricity from chp and the grid compared to electricity from pv in the emissions- and exergy-optmisations.

The exergy-results in the emissions-optimised renewable-based scenario are higher than for the exergy- and price-optmisations due to the higher use of electricity from pv for the supply of heat. The low exergy-results for the exergy-optmisation stem from the high amount of energy supplied by the solar thermal power plant at 30 °C (see Figure 5.2).

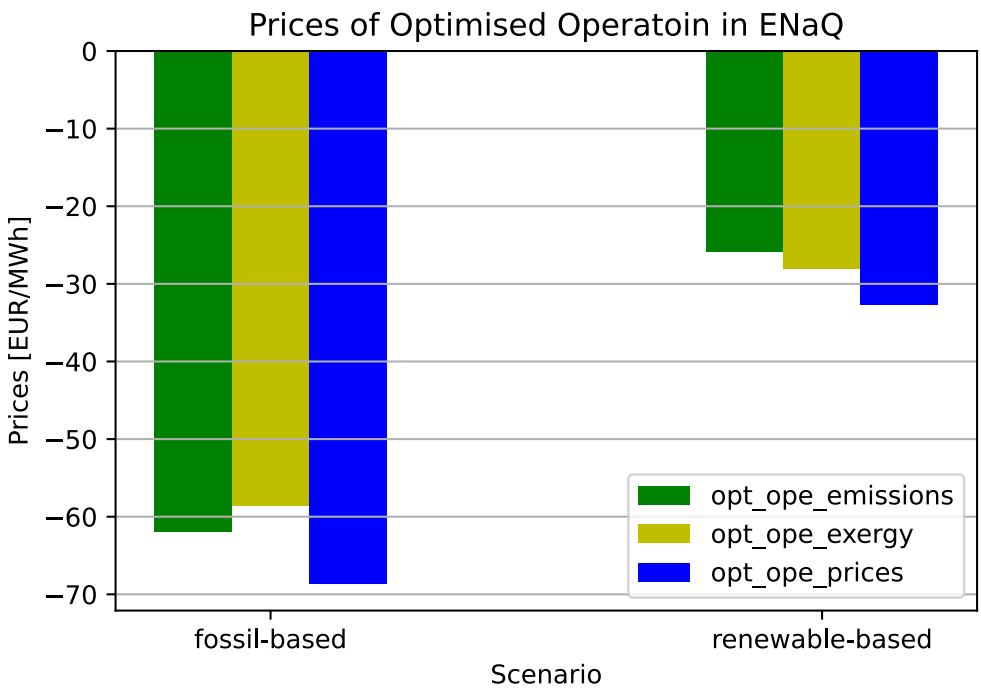

Figure 5.8: results in terms of prices for optimised operations - both scenarios (*opt_ope*: optimised operation for)

In Figure 5.8, I present the results of the optimised operation in terms of demand-specific prices. For each scenario, there are the prices for the optimised operation on all the three KPI: emissions, exergy and prices.

As expected, for prices the price-optimised operation has the lowest values. For the fossil-based scenario the price is −68.66 EUR/MWh and for the renewable-based scenario it is −32.60 EUR/MWh. Negative prices are interpreted as revenue. In the fossil-based

scenario, the emissions-optimisation leads to 9.8 % and the exergy-optimisation to 14.6 % less revenue in terms of prices than the price-optimised operation. In the renewable-based scenario, the emissions-optimisation leads to 20.7 % and the exergy-optimisation to 14.2 % less revenue in terms of prices than the price-optimised operation.

The revenue in terms of prices in the renewable-based scenario optimised for prices are lower than the revenues in the fossil-based scenario - by 52.5 %. This includes only the operational costs and neither the costs for maintenance nor the costs for building the energy systems.

As indicated before, the share of the chp plant in the fossil-based scenario for both, heat and electricity supply, is very high - especially for the price-optimisation. The current economic circumstances lead to a huge advantage of gas-powered energy systems over renewable-based systems. Still, the gas-powered local electricity supply is preferred over electricity supply of the grid - which currently and for the next years also leads to lower emissions than electricity supply only from the grid.

In total, the potential of reduction in emissions for the fossil-based scenario is 12.0 % and for the renewable-based scenario 2.1 %. For the emissions-optimisation this comes with a decrease in revenues of 9.8 % for the fossil-based scenario and 20.7 % for the renewable-based scenario. So, the comparably small improvement in relative emissions comes with a comparably high price for the renewable-based scenario. On the other hand, for the fossil-based scenario there is a quite significant possible improvement through operation and a also quite significant price signal to not make use of this improvement in terms of emissions for the operators. Changing this price signal would be a political task as a huge part of the price differences are subsidies.

Also, an exergy-optimisation for the design of the energy system makes a lot sense, especially for the heat supply system. For the operation an optimisation on exergy leads to comparable but still worse results than an optimisation on emissions. Therefore, an optimisation on exergy for the operation can not be recommended for the optimisation of operation in terms of emissions.

The better results in terms of emissions of the fossil-based scenario need to be relativised and put into perspective with the fact that I use the emissions of the electricity from the grid from 2017. An improvement in the emissions of the power plants that supply the grid electricity would and will (in the coming decades) lead to an improvement of the results of the renewable-based scenario in terms of emissions. Also, a changed design of the local energy system with a higher capability of supplying the full demand renewable-based would lead to better results than the results of the fossil-based scenario.

The results of the optimal operation include hour-specific time series on the energy flows in the energy system. So, which optimal control strategies can I deduce from the optimised energy flows for the three KPI for the fossil-based scenario?

5.2 Deduced Optimal Control Strategies

After presenting the results on optimal operation for both scenarios, I want to present the results on the deduced optimal control strategies for the fossil-based scenario. I thereby answer the first part of my research question and my third guiding sub-question: "*Which optimal control strategies can be deduced for the sector-coupled district energy system of ENaQ [..]?*"

Steering Parameters for Fossil-Based Scenario	
Steering Parameter	Symbol
$\text{demand}_{electricity}$	x_1
$\text{demand}_{heating}$	x_2
$\text{demand}_{warm\ water}$	x_3
$\text{costs}_{grid\ electricity}$	x_4
$\text{irradiance}_{direct}$	x_5
$\text{irradiance}_{diffuse}$	x_6
$\text{temperature}_{ambient}$	x_7
$\text{pv}_{energy\ output}$	x_8

Table 5.1: steering parameters for fossil-based scenario and their symbols in equations

For my deduced optimal control strategies, I use the steering parameters shown in Table 5.1. These steering parameters are the time series that I use for optimising operation. There are no derived parameters included - this could be an improvement for future studies. Derived steering parameters could yield better deduction results and also lead to a smaller number of needed steering parameters and therefore enhanced understandability of the results. In my research group, we discussed for example to include the electrical demand left after the supply through the pv power plant.

Through linear discriminant analysis performed on the training data set of my steering parameters, I obtain the functions shown in Table 5.2. The functions are shown as weights (w) and intercept (i) for the functions (f) specific for electricity (el) or heat (th) and the KPI: emissions (emi), exergy (exe) or prices (pri). With these functions and the respective cut-off-values I can predict for new time series the classes (priority lists) which indicate the preference of a particular technology. So, these functions are my deduced optimal control strategies.

There is no function for the heat of the price-optimisation as the definition of the classes here leads to one class for each point in time. If there is only one priority list for all the time, no function for prediction is necessary.

The weights and the intercepts are rounded to the first significant digit. I only show the result functions with that result in an explained variance ratio of more than 1 %.

Weights (w) and Intercept (i) of Linear Discriminant Analysis Functions (f)						
no	$f_{el,emi}$	$f_{el,exe}$	$f_{el,pri,1}$	$f_{el,pri,2}$	$f_{th,emi}$	$f_{th,exe}$
w_1	$-6*10^{+1}$	$+1*10^{+2}$	$-2*10^{+2}$	$-3*10^{+2}$	$-2*10^{+1}$	$-6*10^{+1}$
w_2	$+5*10^{+0}$	$+7*10^{+2}$	$+8*10^{+2}$	$+8*10^{+2}$	$+7*10^{+0}$	$+1*10^{+0}$
w_3	$-8*10^{+0}$	$-5*10^{+2}$	$-5*10^{+2}$	$-5*10^{+2}$	$-5*10^{+0}$	$-6*10^{-1}$
w_4	$-1*10^{+1}$	$+2*10^{+2}$	$-1*10^{-1}$	$-2*10^{-1}$	$-6*10^{+0}$	$+2*10^{+0}$
w_5	$-3*10^{-4}$	$-1*10^{-1}$	$-1*10^{-1}$	$-1*10^{-1}$	$+2*10^{-3}$	$+1*10^{-3}$
w_6	$-7*10^{-3}$	$-2*10^{-1}$	$-3*10^{-1}$	$-3*10^{-1}$	$-5*10^{-3}$	$-4*10^{-3}$
w_7	$+8*10^{-3}$	$+1*10^{+1}$	$+1*10^{+1}$	$+1*10^{+1}$	$-1*10^{-2}$	$-1*10^{-1}$
w_8	$+2*10^{+2}$	$-1*10^{+2}$	$+1*10^{+2}$	$+2*10^{+2}$	$+1*10^{+2}$	$+2*10^{+2}$
i	$+9*10^{-1}$	$-2*10^{+3}$	$-2*10^{+3}$	$-2*10^{+2}$	$+2*10^{+0}$	$+2*10^{+1}$

Table 5.2: weights and intercept of linear discriminant analysis functions (*el*: electricity, *th*: heat, *emi*: optimised for emissions, *exe*: optimised for relativ exergy-input, *pri*: optimised for prices)

The focus of this thesis is not to analyse and find the best steering parameters but to find a deduction method that is suitable to identify optimal control strategies that lead to good results in terms of KPI. The results for the different KPI are analysed in section 5.3. Nonetheless, I want to add a critical comment on the analysis of the relevance of the steering parameters through the weights of the functions: The significance of each steering parameter can not be interpreted from the functions easily. A smaller number for the weight of the first term compared to the fourth term might also be due to higher values of the steering parameter of the fourth term. Nonetheless, some comparisons are possible. For example, the change of significance of one steering parameter for the different optimisations and for electricity and heat can be seen directly for all steering parameters apart from the fourth steering parameter. The fourth steering parameters are the costs of the grid electricity which change depending on the optimisation goal. In this case, only the functions with the same optimisation goal can be compared directly. Also, the time series of the steering parameters themselves have an important role in their significance: Even if the weights are big, a time series might change a lot over time or only twice a year. So a huge importance in terms of weights does not necessarily reflect on a huge steering effect of the steering parameters.

As I do not perform a profound analysis of the steering parameters, there might and probably still will be some insignificant steering parameters in the functions. In future research a task could be to reduce the number of steering parameters and thereby obtain steering functions that are easier to interpret.

In Table 5.3, I show the shares of correctly predicted classes by my deduced optimal control strategies (the functions obtained from linear discriminant analysis including their cut-off-values) for both, only the test data and the whole data set.

Correct Prediction Shares of Linear Discriminant Analysis Functions (f)						
Data Set Used	$f_{el,emi}$	$f_{el,exe}$	$f_{el,pri}$	$f_{th,emi}$	$f_{th,exe}$	$f_{th,pri}$
Test Data	91.6 %	91.3 %	79.0 %	90.0 %	92.8 %	100.0 %
All Data	91.0 %	91.7 %	79.2 %	90.4 %	92.5 %	100.0 %

Table 5.3: shares of correct prediction for test and whole data sets (*el*: electricity, *th*: heat, *emi*: optimised for emissions, *exe*: optimised for relativ exergy-input, *pri*: optimised for prices)

The results do not differ more than 0.6 percent points. In two cases the prediction of the test data is better and in three cases the prediction of the whole data set is better. I therefore conclude that validating my deduced optimal control strategies with the whole data set (section 5.3) yields realistic results as my functions are not over-fitted to the training data set.

With my deduced optimal control strategies I know have two priority lists per optimisation goal: one from the class definitions and one from the classification with the functions from the linear discriminant analysis. In the next section, I want to show how well both of these priority lists perform in terms of KPI compared to the optimised operations.

5.3 Validation of Optimal Control Strategies (Revised)

My fourth guiding sub-question is answered in this section: "*How good are the simulation results obtained with the optimal control strategies [..] compared to the optimal operations [..] in terms of KPI and greenhouse gas emissions?*" I therefore use the priority lists from section 5.2 for the fossil-based scenario.

As a critical comment, I want to remind that the priority lists do not include the heat storages. The heat storages are used significantly in the optimised operation (see Figure 5.2 and Figure 5.3). For the validation, the heat storages are still optimised by the solver and not steered by the deduced optimal control strategies. Therefore, the results presented in this chapter are better than what could be obtained under real conditions. Adding the heat storages to the deduction and assigning a priority to them as well could improve this in future research.

In Figure 5.9, I show the KPI-results in terms of emissions for the optimisations: the optimised operations (*opt_ope*), the optimisations with the priority lists based on the class definitions (*prio_class_definitions*) and the optimisations with the priority lists based on classification with the deduced optimal control strategies (*prio_classification*). For each of the three cases, I show the results in terms of emissions for each of the three optimisation goals: emissions (*opt_ope_emissions*), exergy (*opt_ope_exergy*) and

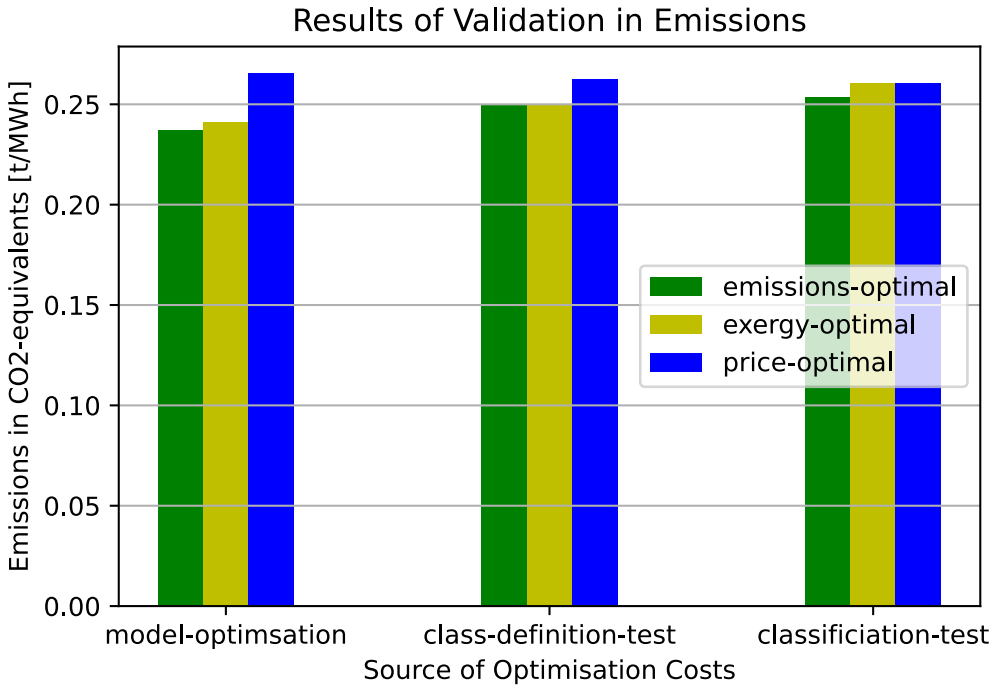

Figure 5.9: optimisation-goal-specific results of validation in terms of emissions for optimised operations and deduced optimal control strategies (*opt_ope*: optimised operation, *prio_class_definition*: priority lists based on class definitions, *prio_classification*: priority lists based on classification with the deduced optimal control strategies)

prices (*opt_ope_prices*).

In optimised operation and taking the results for optimising on emissions as 100 %, the exergy-optimisation leads to 1.6 % and the price-optimisation to 12.0 % higher emissions. None of the results from the control strategies via priority lists is better than the exergy-optimised operation or worse than the price-optimised operation. This indicates that there is improvement potential for the emissions through control by priority lists compared to model-optimised operation with the goal of low prices. The best result obtain the emissions- and the exergy-optimal control steered by the class-definition-based priority lists with 5.5 % and 5.4 % more emissions than the emissions-optimal operation. The worst result obtains the price-optimal control steered by the classified priority lists with 10.9 % more emissions.

The emissions- and exergy-optimal control yields better results in terms of emissions for the class-definition-based priority lists than for the priority lists based on the classifica-

tion. This indicates that the classification is not optimal yet. With 6.8 % compared to the 5.5 % in the class-definition-based priority lists higher emissions than in the model-optimisation, the classification yields satisfactory results though.

The exergy-optimal class-definition-based priority lists yield slightly better results than the emissions-optimal ones. This indicates that the class definitions are not optimal yet and that there is improvement potential - in this case of the assigning of energy system states described as conditions to classes (see subsection 3.2.1). With 0.1 %points, this improvement potential is quite low though.

Concluding on the results on emissions, the deduced optimal control strategies have a potential for improvement in terms of emissions. They are even better than the price-optimised model with all the data on the future. Nonetheless, the results are - as expected - worse than the emissions-optimised model. Also, it is not clear how big the impact of the heat storage is which is for the results still optimised by the model. Before drawing a final conclusion on the deduced optimal control strategies, I want to present the results in terms of exergy and prices.

The results in terms of exergy shown in Figure 5.10 are similar to ones in terms of emissions (Figure 5.9).

In optimised operation and taking the results for optimising on exergy as 100 %, the emissions-optimisation leads to 1.0 % and the price-optimisation to 10.1 % higher relative exergy-input. None of the results from the control strategies via priority lists is better than the emissions-optimised operation or worse than the price-optimised operation. This indicates that there is improvement potential for the exergy through control by priority lists. The best result obtains the exergy-optimal control steered by the class-definition-based priority lists with 4.1 % more relative exergy-input than the exergy-optimal operation. The worst result obtains the price-optimal control steered by the class-definition-based priority lists with 8.9 % more relative exergy-input.

In Figure 5.11, the results in terms of prices are shown.

Taking the revenues from price-optimised operation as reference and 100 %, the emissions- and exergy-optimised operations lead to 9.8 % and 14.6 % less revenue.

Interestingly, the results for the deduced optimal control strategies for the optimisation on emissions and exergy are significantly better than the emissions- and exergy- optimised operations in terms of prices. For the emission-optimisations, the class-definition-based priority lists reach a revenue that is only 8.0 % and for the classification based priority lists a revenue that is 7.3 % lower than the revenue in the price-optimised operation. For the exergy-optimisations the values are 11.9 % and 5.0 % respectively.

Also, the price-optimal deduced control strategies perform very well compared to the

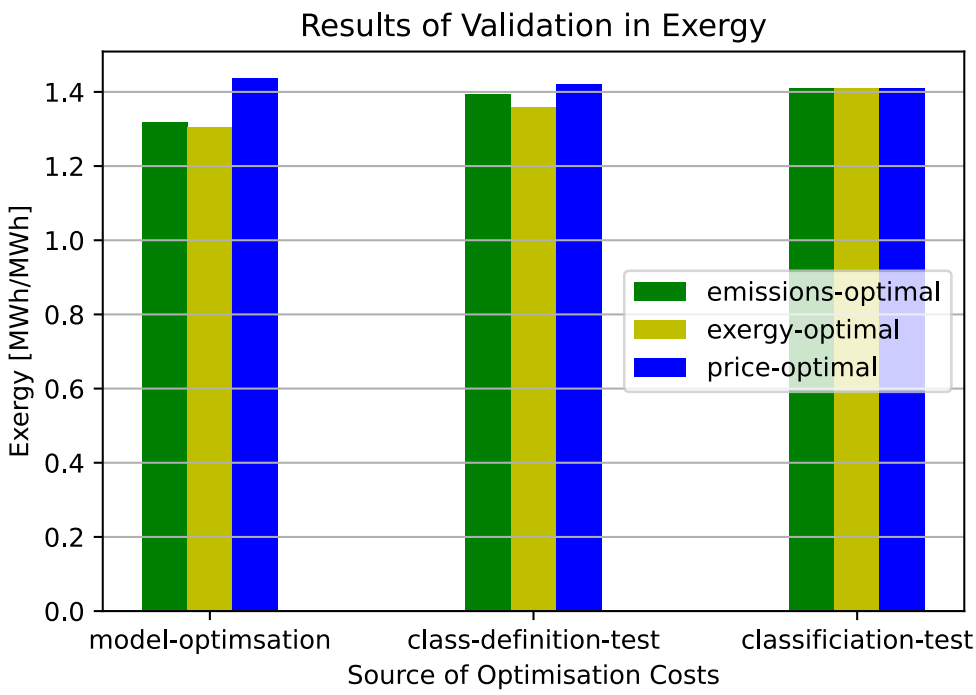

Figure 5.10: optimisation-goal-specific results of validation in terms of relative exergy-input for optimised operations and deduced optimal control strategies (*opt_ope*: optimised operation, *prio_class_definition*: priority lists based on class definitions, *prio_classification*: priority lists based on classification with the deduced optimal control strategies)

optimised operation. For the class-definition-based control strategies the revenue is 2.1 % lower than the one of the price-optimised operation. For the classification-based control strategies the revenue is only 5.0 % lower.

Evaluating the deduced optimal control strategies from an emissions- and price-perspective in comparison to the optimised operations, they perform quite well. For the emissions-optimised deduced control strategy compared to the emissions-optimised operation, the emissions increase by 6.8 % but therefore the revenues also increase by 2.9 %. For the price-optimised deduced control strategy compared to the price-optimised operation, the emissions decrease by 2.0 % but therefore the revenues also decrease by 5.0 %.

Concluding on the performance of my deduced optimal control strategies, their performance is well. A final judgement if the approach is applicable under real conditions is impossible as the validation is still done with oemof and therefore data about the future and model-optimised heat storages. Nonetheless, the results for the validation support

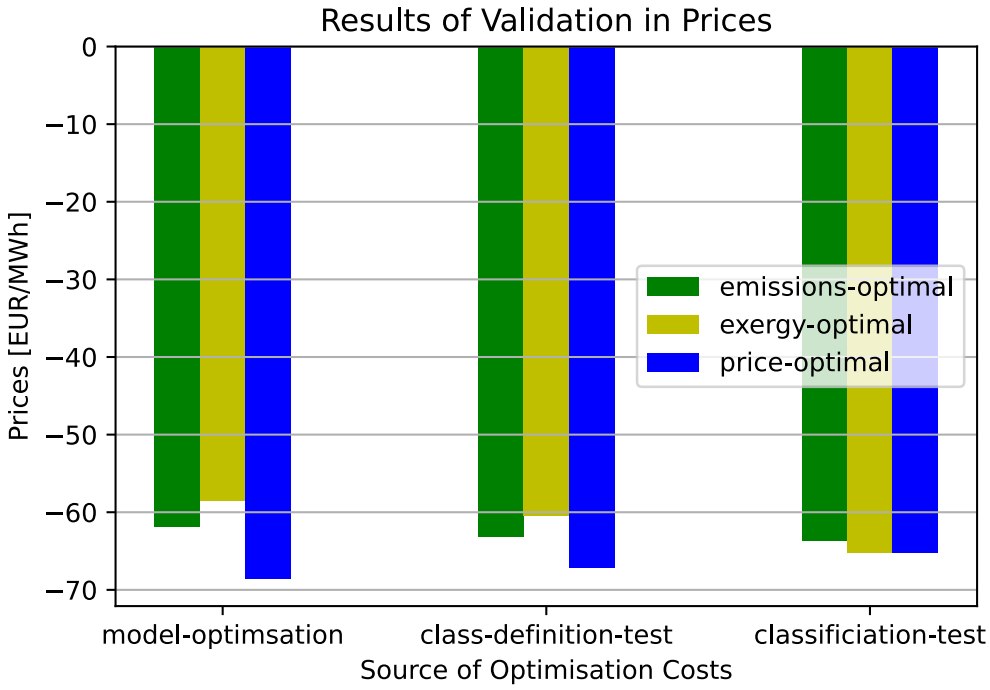

Figure 5.11: optimisation-goal-specific results of validation in terms of prices for optimised operations and deduced optimal control strategies (*opt_ope*: optimised operation, *prio_class_definition*: priority lists based on class definitions, *prio_classification*: priority lists based on classification with the deduced optimal control strategies)

the potential of the deduced optimal control strategies to perform well.

Concluding on the improvement potential of the deduced optimal control strategies, it seems that the classification works well. The classes seem to be well-defined, with one exception with slight improvement potential, and the classification yields good results.

Collecting the outcome of my research: What are my key findings? What needs to be critically reflected? And which recommendations can I make for future research? These questions are answered in the next chapter.

6 Conclusion

In this chapter, I summarise my key findings (6.1), critically reflect my outcome (6.2) and give recommendations for further research (6.3).

6.1 Key Findings

In this section, I summarise my key findings with regard to my research question: "*Which optimal control strategies can be deduced for the sector-coupled district energy system of ENaQ and what is their impact on the greenhouse gas emissions of ENaQ?*". My key findings can be split into key findings on the optimal operations as analysis of the improvement potential and key findings on the deduced optimal control strategies.

The analysis of the optimal operations shows that the fossil-based energy system design leads to lower emissions than the renewable-based energy system design for the grid electricity's emissions of 2017. The change of the power plants supplying the electricity in the grid in Germany in the next years will significantly impact on these results. Also, a renewable-based energy system with a higher degree of autarchy and thereby less use of electricty from the grid would improve the results of the renewable-based scenario. For the fossil-based scenario, there exists a significant potential for improvement when optimising the operation for emissions and not for prices which comes with a reduction in revenue in the same relative dimension. This means that the current price signal steers in the direction of not using the potential for reduction of emissions. For the renewable-based scenario, the relative potential of reduction of emissions is around ten times lower than the relative reduction in revenues it comes with. An exergy-optimisation for operation yields better results in terms of emissions than the price-optimisation but slightly worse results than the optimisation on emissions.

For all KPI, a deduced optimal control strategy with better results in terms of emissions than the price-optimised operation could be found. Due to the method of validating with the oemof-model, a final conclusion on the performance of the deduced optimal control strategies under real conditions cannot be made. This is majorly due to the facts that the heat storages are not part of the priority lists and that the validation is performed with oemof and therefore information about the future. Nonetheless, the results of the

validation of the deduced optimal control strategies indicate that their performance is well and that the method could perform well under real conditions. This conclusion is valid for both, the approach of priority lists as classes as well as the method of linear discriminant function analysis for classification.

What should be seen critically in my research? This shall be the guiding questions for the next section.

6.2 Critical Reflection

In this section, I want to summarise the most critical parts of my research.

First of all, I want to name the most important research boundaries: Mobility is not included in my research. My research is based on data for the reference year of 2017 which is particularly important for the emissions of electricity from the grid. I only have a look on the three KPI emissions, relative exergy-input and prices - which excludes other impacts of a local energy supply system like autarchy, social and environmental impact of the energy system over its full life cycle or decentralisation of the energy system in Germany as a whole. The design of the energy system is also not part of my research. This means that no costs for manufacturing, installation or end-of-life are included, neither for costs in terms of emissions nor for costs in terms of prices.

The optimal control strategies are deduced with training data and then validated with testing and training data together. Although the results of the prediction of the testing data compared to the testing and training data seem to be comparable, this can be another source of error or over-estimation of performance of the deduced optimal control strategies.

The validation of the deduced optimal control strategies is done with oemof and therefore information about the future as well. This leads to results from which it is not possible to conclude whether a control strategy is under real conditions usable and applicable. Also, the control with eight steering parameters leads to a lower chance of re-use for the deduced optimal control strategies for other energy system designs. Therefore, the goal of a under real-conditions usable control strategy is achieved - but a final statement of its performance can not be made.

How would I recommend to continue from my research?

6.3 Recommendations for Further Research

There are some relevant parts out of the scope of my research which I recommend to include in further research at some point. I think that other KPI are relevant for the operation of local energy supply systems. The social and environmental impact of a local energy supply system throughout its full life as well as the potential for decentralised solutions that increase the independence of the households should, from my perspective, have a prominent role in the discussions and decisions on local energy supply systems in Germany. Also, including mobility in the analysis of local energy supply systems is important for a successful energy transition that reaches the goal from the Paris Agreement. For the ENaQ-project, analysing the actual energy system that is decided on is from my perspective the next important step.

With regard to the outcome of my research, I recommend to further work on the deduction method. First of all, all technologies should be included in the deduction - in my case this includes the heat storages. This would allow a validation that is not based on information about the future and therefore a more realistic conclusion on the performance of the deduced optimal control strategies. Also, I recommend to increase the amount of potential steering parameters. For example, derived steering parameters like the electrical demand minus the supply of the pv power plant could be interesting. In order to increase the ability to re-use and interpret the deduced optimal control strategies, I recommend to further reduced the amount of steering parameters to the most significant ones as well.

And, most importantly, I want to emphasize the importance of further research that is value-based and goal-oriented - for example driven by the motivation to reach the goal of the Paris Agreement, the Sustainable Development Goals or to mitigate global injustice in the supply chains and end-of-life phases of the local energy supply systems installed in Germany.

In the following, I give you a list of my references and add some comments on the contexts in which I have written this thesis.

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Afterword

With these words after the thesis I try to give you, the reader, an overview about and insights into:

- the organisation I worked at during my thesis, the DLR-VE. (About the Organisation: DLR - Institute of Networked Energy Systems)
- the study programme I have studied in, the Postgraduate Programme Renewable Energy. (About the Study Programme: Postgraduate Programme Renewable Energy)
- the writing process and how I prepared this thesis. (My Writing Process)
- the things I learned during the writing process that I would like want to share with you. (My Lessons Learned)

About the Organisation: DLR - Institute of Networked Energy Systems

The German Aerospace Center (DLR) is the national aeronautics and space research centre of the Federal Republic of Germany. Its extensive research and development work in aeronautics, space, energy, transport, security and digitalisation is integrated into national and international cooperative ventures. In addition to its own research, as Germany's space agency, DLR has been given responsibility by the federal government for the planning and implementation of the German space programme. DLR is also the umbrella organisation for one of the nation's largest project management agencies. DLR has approximately 8 000 employees at 20 locations in Germany.

The DLR-VE was founded in 2007. In Figure 6.1, its main building is shown. The DLR-VE has around 150 employees. In 2018 the budget of theDLR-VE was 14.7 million euros out of which 47 % were third-party and 53 % institutional funds. The DLR-VE has three departments:

Figure 6.1: main building of the Institute of Networked Energy Systems (photo: DLR)

- Urban and Residential Technologies
- Energy Systems Technology
- Energy Systems Analysis

My position in DLR-VE is located within the department *Energy Systems Technology* in the working group *Energy Management*. The project I am part of is *ENaQ*.

About the Study Programme: Postgraduate Programme Renewable Energy

"Starting in 1987, the Postgraduate Programme Renewable Energy (PPRE) has graduated more than 563 participants from $\tilde{8}5$ countries in over 30 years.

Students (who must hold a 6-semester (180 CP) Bachelor's degree in engineering or science in order to be admitted) with some professional experience in the field of energy study the theory and applications of renewable energy systems, test their skills in labs and outdoor experiments, visit companies and sites, and do an external training in industry or research institutes. The programme is completed with a thesis project.

Successful participation is awarded with an MSc [Master of Science] degree. PPRE's alumni made their careers in industries, consultancies, government bodies, NGOs [Non-Governmental Organisations] or in research institutes.

The university keeps good contacts to alumni, who are taking part in regional seminars or are invited to give lectures for the present students. Networking with alumni includes a newsletter, e-mail distribution lists, internet platforms and visits.

The programme has cooperation agreements with universities abroad with the aim of intensifying the exchange of staff, students and curricula in the field of postgraduate renewable education." [50]

Figure 6.2: Energy Laboratory at the University of Oldenburg

To highlight it: PPRE and the Energy Laboratory (E-LAB) which you can see in Figure 6.2 are very special. Started in 1987 PPRE is one of the oldest study programmes fully focused on renewable energy in the world. Its alumni network is, to my knowledge, unique in the world - in terms of geographic diversity and time horizon. The E-LAB, where I started studying in Oldenburg, is unique as well. Its photovoltaic modules started operation in 1976 [51, p. 9] and were moved to the E-LAB in 1981 - until today that sums up to 44 years of operation.

My Writing Process

After introducing my working context at DLR-VE and within PPRE, I want to give some insights in my writing process. Throughout the six months of writing my thesis, I have written a learning diary with one entry every two weeks which I want to present month by month.

In the first month, I wrote my exposé and arrived at DLR-VE. At DLR-VE, I was part of the department "*EST*", the working group "*EM*" and the project "*ENaQ*". In this month, I decided to take my thesis as learning opportunity with the focus on *Python*, *oemof* and *LaTeX* software skills. I also decided to only work with free and open source software like *git* for version control, *Zotero* as reference management system, *Overleaf* as LaTeX-editor, *Spyder* as coding environment, *gantt-project* for my time management, *LibreOffice* to write my exposé and *Inkscape* to work on vector-graphics. Within python I use the free and open source packages (in alphabetical order) *dateutil*, *matplotlib*, *networkx*, *numpy*, *oemof.solph*, *oemof.thermal*, *os*, *pandas*, *pygraphviz*, *sklearn* and *sys*.

In the second month, I started to build my fossil-based energy system model in oemof. In this month, the Corona-pandemia started and from there on, I wrote all my thesis from home.

In the third month, I started appreciating the frequent and for me most important meetings at DLR-VE. Every week, there were a meeting with my supervisors Patrik and Herena and my project leader Peter as well as an ENaQ-project meeting. These meetings helped me a lot to stay motivated, get to know the context of my thesis and how my results can be further used and to learn through discussions. Every second week, there were meetings within the group and department which helped me to get to know my colleagues and other work at DLR-VE. In this month, I also defined the starting point of my research on how to deduce optimal control strategies from optimised operations. I also created many explanatory figures for my methods and data as solid foundation for discussions and my thesis. Much of my input data, I collected it in this month.

In the fourth month, I finished the oemof-models of my two energy systems. I also defined my deduction approach as classification. In this month, I noticed that I was a bit behind my originally scheduled timeline as the building of the energy system models took me more time than expected. A success factor in these weeks for me was to split huge working packages in smaller ones that I could finish within days or a week in order to make my progress visible for myself. Another success factor was to always try to solve problems for myself first - but if I got stuck for more than some hours, I asked my supervisors and received well support. The trying was good for my learning process while the help was good for my thesis progress.

In the fifth month, I decided to only deduce optimal control strategies for the fossil-

based scenario and not for the renewable-based scenario as well. Time would not allow me to do both while it was a major goal of my thesis to show the method, potential and performance of the deduction. Due to its lower complexity, I decided with my supervisors to deduce the optimal control strategies for the fossil-based scenario. In parallel to that, I prepared the results on the optimal operations and started to write the first parts of my thesis, especially the methodology and the data chapters.

In the last month of the thesis, I mainly wrote the thesis but also finished the deduction of optimal control strategies and their validations.

My Lessons Learned

During my time at DLR-VE, I learned a lot about indicators. I like their different functions in decision, coordination, steering and control processes. Also, I learned about the requirements that they should fulfil: completeness, availability, comparability, independence and understandability.

As part of the ENaQ-project, I learned about decision making frameworks for big projects with many partners. Within the ENaQ-consortium, there are the phases of targeting, synthesis, design and operation described for the local energy supply system creation.

I also continued to discuss and reflect on open science. Important buzzwords for me in this context are "*public money, public results*", *open access journals* and *open data and repositories*. For myself, I can say that I strongly support the open science movements.

The competence exchange within the employees at DLR-VE also gave me many things to learn. I notice that bundling competencies within departments and groups with frequent meetings so that everyone knows what others do, know well and who they are combined with creating exchange and discussion platforms in projects and shares offices for the every day work lead for me to a huge support-infrastructure and decentralised as well as a learner-centered learning environment. At the same time, an organisation with the size of the DLR-VE comes with the risk of responsibility diffusion, growing hierarchies and bureaucracy - and therefore the need to frequently reflect on these topics. Both, the positive and the negative aspects, I want to keep in mind for my future work.

During my work on the thesis I came across "*data management plans*" and "*linked open data*", the latter in the form of a reference graph that shows how different studies that I build my work on are related and where the roots of my thesis come from. For future research, I do not only want to try to purely or mainly work with openly accessible resources but as well want to try to implement a data management plan an make the links between my thesis and my references more transparent with a reference graph.

Thanks a lot for taking the time to read my thesis. I hope to have contributed a tiny bit to one of my main goals that I already cited in my introduction: "*[Die] kulturelle Vision der Nachhaltigkeit [...] [ist ein] gutes Leben für zehn Milliarden Menschen auf diesem Planeten [...] ohne die globalen ökologischen [oder planetarischen] Grenzen zu überschreiten*". [11, p. 21] Or the way Tracy Chapman put it: We are "*Talkin' Bout A Revolution*" [52] that is value- and goal-oriented.