Towards rule extraction for sector-coupled energy systems based on optimization models

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Abstract:

Today conventional rule-based control strategies dominate the control of energy systems in urban districts. Due to many interactions in urban districts, commissioning local energy systems and defining rules for optimal setpoint control is a challenge. Currently, expert knowledge based on comparable systems serve as basis to set up increasingly complex controls. Moreover, this process is becoming increasingly challenging due to the growing use of technologies such as heat pumps or storage systems to increase the share of renewable energies in the building energy sector. In academia complex systems are often controlled via computationally intensive methods such as model predictive control. Disadvantages are the complex initial commissioning, high computing demands, and a lack of interpretability of the system's behavior. To capture the complex interrelationships, the proposed method extracts simple rules from artificial optimal control. The energy system is first represented by a mathematical optimization model. The model determines the optimal plant operation for given demand time series. The optimization results are fed into white box machine learning models, such as Decision Tree Classifiers, to determine the revalent influencing factors and dependencies that are decisive for the determined operation. The process yields the relevant variables and setpoints for a simplified rule-based control. The extracted rules for an existing energy system are validated against the existing rule set and the theoretical optimum according to the optimization results by simulation. The rules can be interpreted by technical staff and applied to existing programmable logic controllers. This study introduces a toolchain to automate the creation of rule-based controls for complex energy systems.

Keywords:

rule-based control, optimization, machine learning, energy hub, sector-coupling, district energy system

1. Introduction

In order to achieve the climate targets that have been decided in the European Union, the emissions in CO2 equivalents in the building sector and here in particular also the direct emissions through the heating, cooling and electricity supply must be reduced. [1] To this end, renewable energies are increasingly unsed and integrated into existing energy systems in order to cause fewer emissions from fossil fuels. In the course of the energy transition in the building sector, control of the energy systems play a crucial role, as large potentials are wasted by inefficiency, but also the control of energy systems becomes more complex due to the use of new generation plants, the coupling of sectors and the integration of volatile renewable sources. [2]

The control complexity of an energy system increases with the following characteristics:

- The use of different generators.
- Coupling of sectors and inter-dependencies of sectors and generators.
- Different minimum loads of generators.
- Size and use of storage.
- Integration of own renewable generation such as photovoltaic (PV).
- Variable electricity and gas prices, as well as variable revenues for supply of surplus electricity to the public power grid.
- Utilization of flexibility for grid efficiency in the electricity sector.

Some of the listed factors offer the potential to make the provision of heating, cooling and electricity more efficient and to improve the integration and utilization of renewable energy sources. Due to the complexity of these systems, potentials may remain unused if no benefit is derived from the potentials in practice through simple control strategies.

https://doi.org/10.52202/069564-0292

In practice, the setup of the controls of complex energy hubs [3] that contain different generators coupling the heating, cooling and electricity sectors is an individual and time consuming task. For simple energy systems, containing only few units for energy supply and storage, it is feasible to find a standard procedure that is applicable on multiple reoccurring systems and control problems. With rising complexity and rising demands on the control of modern energy systems there are no normative or systematic procedures to setup the controls. Advanced control strategies, that are promising for complex control tasks, like model predictive control (MPC) or reinforcement learning (RL), have not yet made a leap into broad real world application due to implementation and acceptance barriers. [4] [2] Rule-based-control (RBC) operation is often based on the experience of the technician and individual considerations of the production costs for heating, cooling and electricity by the plants used. These are then implemented by a technician, for example, in the form of a generator sequence control. A common procedure for optimizing the energy system is to evaluate the current operation supported by monitoring and to determine control parameters in an iterative process, to yield satisfactory operation. This is measured and evaluated by the plant operator on the basis of key performance indicators such as the average operating point, efficiencies and prevention of short cycling of the plants.

The present work demonstrates a systematic procedure for deriving feasible operating rules for RBC of a district energy hub, that provides heating, cooling and electricity. The idea is based on the calculation of the theoretical optimum operation by means of mathematical optimization, taking into account dynamic boundary conditions and influencing variables. The results are then analysed in order to derive control rules for the supervisory level of the RBC. This is intended to circumvent barriers of complex control methods such as MPC in order to realize short-term potentials by improving the control of energy hubs in practice.

2. Literature Review

In this section selected sources dealing with rule extraction methods for energy systems in general are used summarize different methods for optimizing RBC systems. Furthermore examples of successful applications are given and challenges are adressed to identify open research questions.

May-Ostendorp et al. have discussed the possibilities of rule extraction from the results of an offline MPC in [5], [6] and [7]. In each case, the goal was temperature control in buildings using extracted rules from a training dataset containing time series data from an offline MPC. A distinction between closed-loop and open-loop learning is introduced in [6]. The closed-loop approach describes how time series data that is extracted from a system with a closed MPC loop with feedback and disturbances from the system is used to train the behavior of this MPC. In the open-loop approach, training is based on optimization results, which are used separately from the system and the actual control. The use cases described by May-Ostendorp et al. each include the building automation system and various parts of the indoor air conditioning system. The generator side is not considered. The derived rules are interpretable and were successfully tested on the building automation system for the studies.

Maier et al. [8] and Yang et al. [9] use Machine Learning (ML) models to approximate the controller behavior of a MPC. This kind of control is also referred to as approximate MPC (AMPC). The methodology of the studies can therefore be classified as closed-loop learning. The primary goal of these studies is to reduce the complexity for implementation in practice. Maier et al. uses a system to supply heating and cooling to a building using a heat pump and thermal storage. With a training data set of 2 years, it was possible to mimic the discrete modes that the MPC specifies for operation. Yang et al. uses a recurrent neural network (RNN) to learn the MPC behavior for a building's HVAC system. While the AMPC model achieves promising cost savings, the MPC is more able at ensuring comfort in the building.

Drgoňa et al. [10] use miltivariate regression algorithms to emulate optimization-based MPC. It is a closed-loop learning approach, which is demonstrated on the example of the control of a multi-zone building. The approximation of MPC yields very good results with the deep time delay neural networks (TDNN) and regression tree (RT) models employed. The application is successfully implemented and demonstrated on embedded hardware in the study.

Domahidi et al. [11] describe rule extraction using a closed-loop approach. Here, binary decision rules are extracted for the supervisory level of a building automation system using the ML models SVM and AdaBoost. Péan et al. [12] compare in their study different control concepts to exploit flexibilities of heat pump systems on the supervisory control level. The use case is the provision of flexibility for the public power grid. Studies with RBC and MPC are compared and it is shown how far RBC can also be used for control with the flexibility objective.

Robillart et al. [13] use the statistical method beta regression to learn from the optimization results. The use case is a residential building which is heated electrically and dynamic electricity tariffs are exploited by load shifting. The results show that the optimal behavior could be reproduced well under drastic reduction of the computing capacity and also outperforms a simple heuristic control.

In their study, Yu et al. [14] use a two-stage ML procedure to extract interpretable rules from a simulated MPC using an EnergyPlus model. Therefore the approach is a closed-loop-learnning procedure. The results of the multi-objective optimization are first clustered by an unsupervised clustering procedure to identify recurrent control decisions. In a second step, a decision tree classification is then used to reassign the clusters to the corresponding initial situations in the space for control. The method shows only slightly lower performance for the control of room air conditioning for the use case compared to the MPC, which serves as a reference.

Kanwar et al. [15] compare a MPC and a RBC approach for a microgrid that includes PV systems and decentralized storage systems. The control approaches are intended to control the microgrid in such a way that the fluctuating renewable generation is self consumed and the degree of energy utilization is increased via the storage system. The MPC approach shows the best results due to the optimization with included predictions for renewable generation. Here, the rule-based approach consists of if-then-else loops based on engineering considerations that control the system depending on storage levels and electricity prices.

In general, the procedures in the literature can be divided into open-loop and closed-loop procedures as described by May-Ostendorp et al. [6]. The presented studies can also be subdivided with respect to the rule extraction procedure and the applied ML models. On the one hand, there are studies that apply rule mining to directly extract rules and limits for a rule-based system. For this purpose, ML models are used that establish interpretable relationships, such as decision tree classifiers and clustering algorithms. On the other hand, there are studies that aim to approximate the behavior of MPC using the ML models and replace the online MPC with a meta-model, which can significantly reduce the computational effort. For this method, ML models can be implemented on low level hardware to interact and control the energy system. In this case no interpretable relationships between input and output of the controls are given.

The application fields of the literature presented here describe, among others, building energy systems and the supervisory level in the building automation system. The control problems to be solved for RBC partly focus mainly on special problems (control of windows [7]) or the control of individual elements of the energy supply system, such as the utilization of storage units [15]. A research gap is identified that addresses control extraction methods for so called ”multiple input multiple output” (MIMO) problems for the coordination of larger energy systems, such as district energy systems and energy hubs with different generators and the coupling of energy sectors.

This study shall showcase the possibilities by describing the energy hub as a mathematical optimization model for the systematic creation of an optimized RBC. In addition, the comparison with existing RBCs implemented by engineers in practice shows that the methodology can also take other variables into account in order to fulfill requirements such as flexibility for the public grid in a rule-based mannor.

3. Use case

The energy system of the presented use case supplies a city district with heating, cooling and electricity. The generation plants are located in an energy hub, the heating and cooling supply of the buildings in the district is carried out via thermal networks. The district is characterized by mixed use, which includes office buildings, hotels, retail, restaurants, industrial enterprises, sports facilities and cultural institutions. The demand profiles show a high simultaneityof heating and cooling demands throughout the year. The connected industry has a year-round cooling demand. Some of the buildings are supplied with domestic hot water via the local heating network. Therefore a year-round heat and cold supply is provided by the thermal networks and the energy hub. In addition to the energy hub, the system is also connected to the public power grid. Some of the buildings have own additional generators for support, such as decentralized heat pumps, which are, however, neglected in this study and are controlled independently of the energy hub. Decisive for the optimization problem are the thermal and electrical loads, which are supplied by the energy hub to the district.

Figure 1 shows the different sectors and all the supplies and demands, that are located in or connected to the energy hub. The heat supply can be provided by different plants.Two combined heat and power plants (CHP) are available, each with a thermal output of 1111 kW and a nominal electrical output of 851 kW, a gas boiler with a nominal thermal output of 1870 kW, a high-temperature heat pump (HT-HP) with a nominal thermal output of 1284 kW, and an electrical heater (EH) with a nominal thermal output of 250 kW. Cooling is primarily provided by two absorption chillers (AC) with a nominal cooling capacity of 787 kW and a heat demand of 1049 kW nominal each. The ACs are connected to free coolers via a recooling circuit, which can also be used as free coolers at outside temperatures below 0℃. The ACs are connected to the free coolers via a re-cooling circuit. The re-cooling circuit of the AC also serves as a heat source for the HT-HP. Due to this coupling, the HT-HP can only be used when the chillers are running, which, however, is always the case due to the high year-round cooling demand as long as the free coolers are not used. While the CHP units are decoupled from the heating network via two buffer storages with a total capacity of 24,000 l, all the other heat generation units feed directly into the heating network. Therefore an optimal sceduling of the devices in regard to current demand, efficiency and minimal part load to reduce on/off cycles is crucial for the control of the energy hub.

https://doi.org/10.52202/069564-0292

The structure of the supply system makes it possible to provide both positive and negative flexibility for the public power grid through appropriate control. This is due to the coupling of the electricity and heat sectors via CHP and HT-HP. The flexibility potentials of energy systems are often achieved with temporary measures, such as the utilization of storage facilities and the thermal inertia of buildings. In this context, only limited amounts of energy can be shifted at certain times. The present energy system can also provide permanent flexibility to the public grid depending on the heating, cooling and electricity demands by shifting the load to other generators. This aspect will be discussed in more detail in the result section 5. when considering different electricity and gas prices as an economic incentive.

The current control is based on a generator sequence, which is carried out via the storage levels of the thermal buffer storage. Currently, the CHP are prioritized to provide the base heat load. The HT-HP is switched on manually when the AC are running and there is a heat demand from the local heating network. The gas boiler and electric heater serve as backup and are used manually in certain situations: If the heat demand from the local heating network and the AC exceeds the capacity of the CHP units, a CHP unit is switched off in favor of the gas boiler, since the gas boiler can provide a higher heat output for the gas used. In addition, the gas boiler serves as a redundancy for, among other unplanned downtime, service times of the CHP units. The electric heater has a relatively low output and is also kept in reserve for peak loads. Although the current control system is largely automated, there are still manual interventions and the limits and prioritization of individual generators are adjusted by a technician in the course to manage an economical operation. This is also the motivation for the methodology to implement a mathematically optimized rule-based operation.

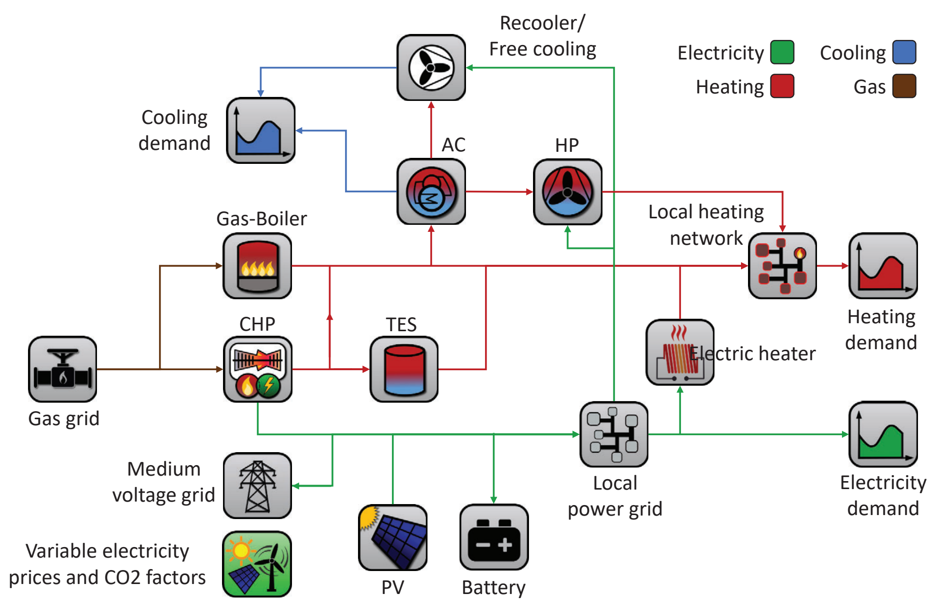

Figure 1: Structure of the sector coupled energy system

4. Methodology

Figure 2 presents the main parts of the methodology. Time series data for heating, cooling and electricity demands, which must be generated by the energy hub serve as input for the optimization model. The time series data must be available for the optimization model in the appropriate temporal resolution. This data can be provided in the form of measurement data from an existing energy system, or from a dynamic building simulation. In addition to the energy requirements, technical and economic constraints are transferred to the optimization model as parameters.

A Mixed Integer Linear Program (MILP) is used as the optimization model. A detailed description of the model is given in section 4.2.. The objective function of the optimization minimizes the operating costs, which, in addition to the costs for purchased electricity and gas, takes into account the revenues for sales to the tenants of the supplied district, as well as lump-sum deductions for start-up costs of the plants and taxes for CO2 emissions. The results of the optimization model are output as a set of time series data per parameter variation. This contains the current outputs of all plants and storage levels for each time step of the optimization. In addition to these raw data, plant performance indicators such as a start-up counter, energy quantities provided and utilization or average operating points are also outputs.

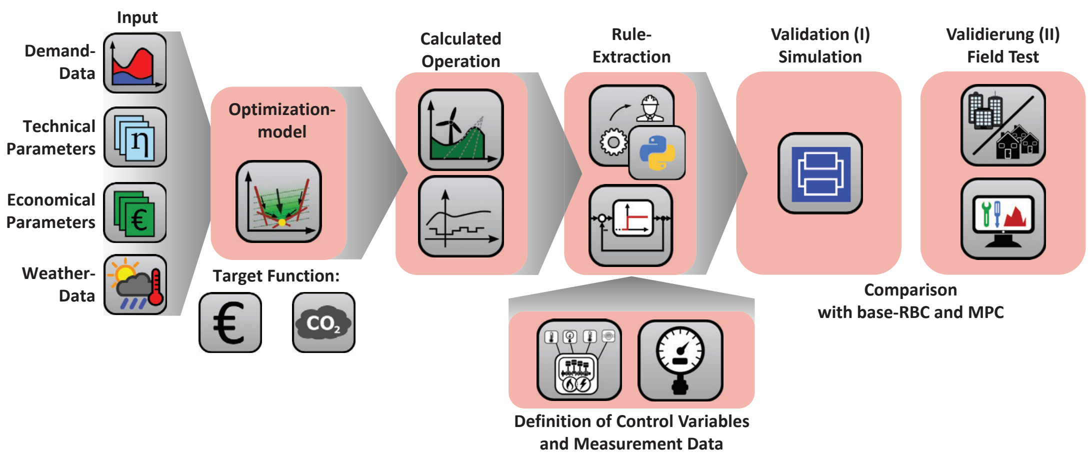

Figure 2: Structure of the Methodology

For the subsequent rule extraction process, the measured datapoints available in the real energy system and the variables to be controlled must be defined. The rule extraction process should use interpretable ML models to establish relationships between the measurable variables and the desired controlled variables for the supervisory level of control of the energy hub implementable by technicians with a corresponding education. In the last step, the rules are validated. On the one hand, an existing simulation model of the energy hub is used, which was implemented in Dymola using the open-source model library AixLib [16]. The comparison can be made in the simulation with the existing RBC of the energy hub, as well as with other control approaches such as an ideal MPC with perfect forecast as an upper-bound comparison. In addition, the rules should also be implemented in practice if they offer potential for improvement compared to the previous mode of operation.

4.1. Data preprocessing

The demand time series for the heating, cooling and electricity demands of the district, which are used for the optimizations, are real measurement data from the project, which were recorded via a monitoring platform. Since cooling can only be provided via the AC, only the heat flow required for the AC, which is recorded via heat meters, is taken into account in order to further simplify the optimization model.

Since data gaps for individual data points occur in the monitoring data set, the time series are subjected to preprocessing. Gaps with a duration of less than 2 hours are closed by the mean value of the adjacent time steps. If a larger gap occurs in one of the time series, the faulty segment removed from the data set. The optimization is then performed for one contiguous segment at a time, with continuity for the thermal storages being maintained by a constraint that the storage levels must be identical at the beginning and the end of each cycle.

4.2. Optimization model

The energy system is formulated as a mathematical optimization problem in Python. The optimization is performed with the commercial solver Gurobi [17]. The coarsest temporal resolution of the underlying measurement data from the real energy system is 15 min. Accordingly, the time step size of the optimization problem is also set to 15 min. The results from the optimization are output as time series data in a structured way.

The main model parameters are described below:

- The thermal and electrical efficiencies of all plants, as well as the coefficient of performance of the HT-HP. The efficiency curve of the gas boiler and the CHP units is approximated by a stepwise linearization, while the EH and the HT-HP are represented by a constant efficiency and coefficient of performance, respectively. Analysis of the measured data shows that the source and sink temperatures of the HT-HP in the application are almost constant, and therefore the assumption of a static COP was assumed to be sufficiently accurate for the case study.
- Minimum partial loads are specified as constraints for all generators.

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- Due to the size of the equipment, special consideration must be given to the cost of wear and maintenance due to frequent start-ups. These start-up costs are provided as parameters in the model. The CHP units are the most expensive with 50 EUR per cycle, the gas boiler and the HT-WP with 10 EUR per cycle each and the electric heater with 3 EUR per cycle. The values were estimated with partners from practice.
- Minimum run times for the following components are specified as constraints: The CHP must run for 30 min, the gas boiler and the HT-WP for 15 min each, and the EH for 1 min before they are allowed to be shut down again by the optimization. In addition to the start-up costs, these constraints were chosen to prevent the plants from cycling and to force a solution with longer run times.
- Generator dependencies in the system were specified by constraints: Due to the high temperatures required for the AC, they can only be supplied by the CHP units or the gas boiler.
- The gas connection is limited to a capacity of 5 MW, which is why only two of the gas-fired plants (Two CHP units and one gas boiler) may be operated at a time.
- The costs for the purchase of electricity from the public grid, the purchase of gas, CO2 emission costs and revenues for the sale of surplus electricity to the public grid are each specified by constant parameters. However, the option is provided to run optimizations via a parameter grid variation. These parameters have a sensitive influence on the optimization result and the use of individual generators. Using the parameter-grid, their influence on the results can be displayed for any time-step and later be used in the automated rule extraction.

The parameters listed were implemented according to the manufacturer's specifications.

The procurement prices for electricity and gas were assumed to be constant, but the model is designed to run optimizations for a parameter grid for different electricity, gas and CO2 prices, so that the influence of these costs on the generation sequence can also be mapped at any point in time.

4.3. Rule extraction

The methodology presented in this paper is intended to provide results through the rule extraction procedure that can be interpreted by a technician and used for setting the control in practice. Therefore, only ML methods that allow this form of interpretation are considered. Existing literature provides examples for the use of Decision Tree Classification, Clustering methods, Support Vector Classification and AdaBoost as discussed in 2..

Currently, two ways are being tested to represent the complex dependencies of this MIMO system from the optimization model in a form that can be directly transferred to the automation system in practice. Enabling of generation units depending on the important decision variables such as current heating and cooling demand, as well as electricity and gas costs can be reproduced using Decision Tree Classification. However, the accuracy of the model trained using optimization data does not yet allow conclusions to be drawn about the performance of the control in practice. Validation is still pending. Another possibility is to transfer the optimization results to operating modes that can also be mapped in the automation system. Thus, the data set can be grouped using clustering. The decisive variables and transition conditions between the modes must be determined in a further step.

4.4. Simulation Model

The simulation model to be used for validation of the optimized RBC is implemented in the Modelica language. It is based on physical models of the simulation library AixLib [16] and is modeled by means of plans for the interconnection of the energy hub, as well as the parameters according to the manufacturer's data sheets. Many of the simplifications in the optimization model, which are based on the simplified mathematical description of the system, are more accurately represented in the simulation model. For example, the model uses fluid models that represent the thermodynamic properties of water. Inertias, as well as start-up processes of the plants and temperature wave propagation in the system are taken into account and the temporal triggering in the model is minute-by-minute. The model contains all interfaces for control using logic expressions in Modelica or for integration as a Functional Mockup Unit (FMU) for co-simulation in another environment, e.g. for embedding in a Python program.

5. Results

The optimization model was tested for several years on measured data and for different model parameters to determine their influence. In particular, a systematic variation of variables that change in reality, such as electricity, gas and CO2 certificate prices, is important in order to learn their influence on the basis of the optimization results for improved control.

For the example plots below, the optimization was carried out for a parameter grid of varying electricity and gas prices. The months of July and December 2021 were used as examples to consider one month in and one month out of the heating period. The plots in figures 3 and 5 each show the relative utilization of the generating units for the heating sector as a percentage. The plots in figures 4 and 6 each show the total operating costs, the revenue generated by selling surplus CHP electricity to the public grid, and the local CO2 emissions generated by the gas-fired plants.

In the month of December, the heat supply for the AC is distributed between the first CHP and the gas boiler depending on the electricity and gas prices. When gas prices are low and electricity prices are high, the first CHP is utilized as much as possible. The second CHP is also partially added when gas prices are low and electricity prices are high. Apparently, the generation of heat and electricity by both CHPs is worthwhile, even if the electricity generation from the CHPs exceeds the captive demand in this case, as shown by the plot of revenues for electricity sales in Figure 4. With increasing gas prices and also decreasing electricity prices, there are parameter pairings that increasingly switch to the gas boiler and also the electric heater for optimal supply. The result is due to the larger amount of heat that can be provided by the gas used through the gas boiler, along with the less economical electricity generation by the CHP units at lower electricity prices. In general, heat generation from the HT-HP is in any case the most economical variant of heat generation for the local heating network, since it is in operation almost continuously high for all variants. Only at the corner of highest electricity costs and lowes gas prices the HT-HP operation is reduced in favor of higher utilization of both CHPs. This is why for the control of the HT-HP, the required waste heat from the AC and sufficient offtake from the local heating network should be decisive and should be preferred to the other generators for heat supply for most cases.

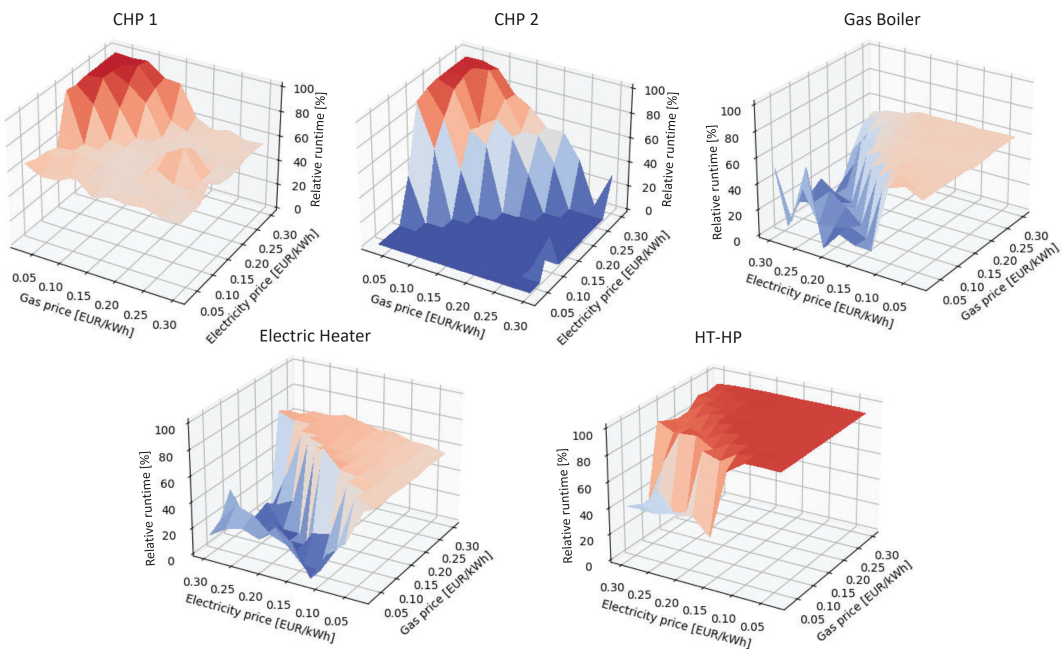

Figure 3: Optimization results for December 2021: Relative runtime of different generators for heating supply

In the month of July, a different generator composition is evident from the plots in figure 5. The share of the second CHP is further reduced for cases of lowest gas prices and highest electricity prices. The gas fueled generators (CHPs and gas boiler) show an only slightly reduced utilization, which is due to the rather constant high temperature heat demand from the ACs that is at a similar level all year round. The heat demand here in July, outside the heating season, is mainly driven by the heat demand of the AC and supplemented from the heat grid only by a small load due to domestic hot water supply. This is clearly evident from the utilization of the HT-HP, which remains at low part load for the entire parameter grid. This can be explained by higher utilization of the generators, which run anyway for the heat supply of the AC, and by the high minimum partial load of the heat pump. Since the heat pump is directly coupled with the heating grid and cannot use a buffer storage volume, a certain minimum demand from the grid is required to operate the HT-HP economically.

The two example months and parameter variations show exemplarily that by a simple analysis of the optimization results rules for the generator enabling can already be derived. In the example, these are dependent on

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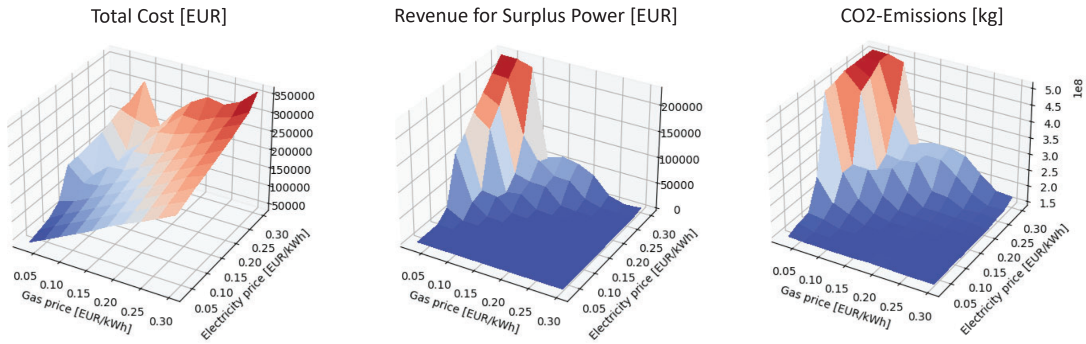

Figure 4: Optimization results for December 2021: Total cost, revenue for surplus power and local CO2-emissions for a parameter-grid of varying gas an electricity costs

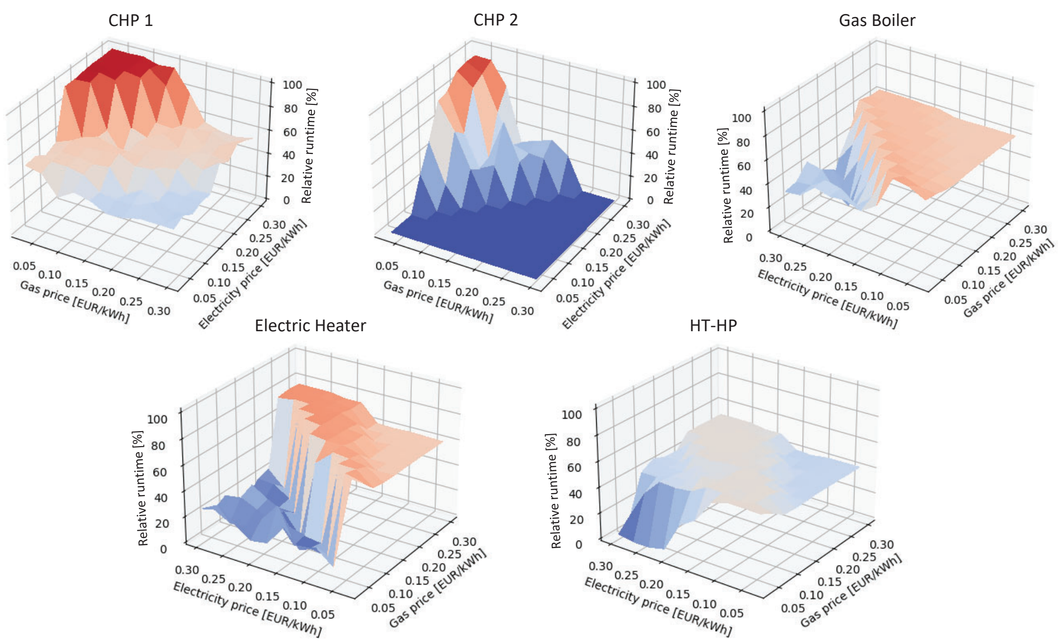

Figure 5: Optimization results for July 2021: Relative runtime of different generators for heating supply

the electricity and gas prices, as well as the season and the correlating heating and cooling demand of the neighborhood and the constraints specified by the model.

The evaluation of different parameter variations shows the dependence of the utilization of individual heat generation plants in the model and the sequence of generators on the influencing variables gas price and electricity price. In particular, if these variables are not fixed in practice by corresponding long-term contracts for periods of time, but are subject to high fluctuations through trading on the energy markets, there is considerable optimization potential here. The previous control-based mode of operation does not include the variable costs described above as decision variables for the control, although in the current situation the prices for electricity purchases and sales are traded directly on the stock exchange. Only gas purchases and CO2 taxes are currently fixed.

6. Summary and Outlook

So far, the study shows the general methodology for systematic optimization of rule-based energy systems using mathematical optimization models. While the mathematical modeling and the representation of the

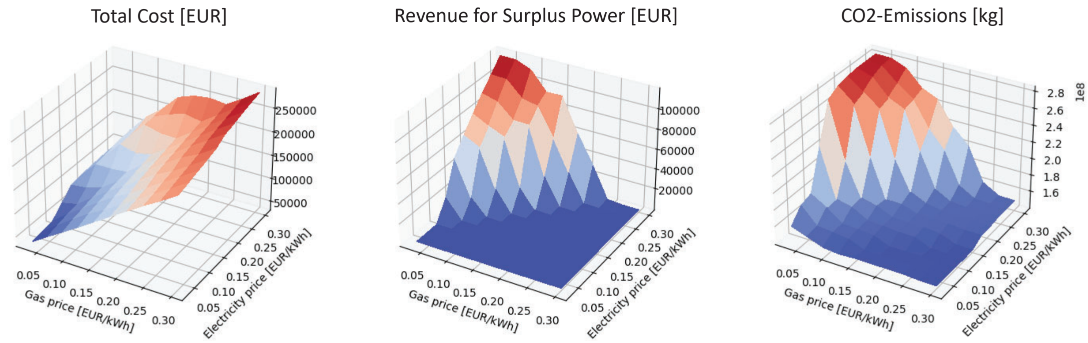

Figure 6: Optimization results for July 2021: Total cost, revenue for surplus power and local CO2-emissions for a parameter-grid of varying gas an electricity costs

energy system using Modelica models have been completed, the automated rule extraction and validation of the entire methodology on simulation and real energy systems are still pending.

The presented methodology can be used to determine the relevant decision variables and extract set-points for an optimized rule-based system, taking into account technical and economic constraints. The iterative procedures for the improvement of rule-based systems, which are common in practice, can be supported by the presented procedure in order to reach an applicable mode of operation faster.

The presented results of the optimization model show exemplarily how the current RBC should be supplemented by further decision variables for the control. Even if validation and the use of automatic control extraction methods are still pending, the influence of variables not yet taken into account in the control, such as the electricity and gas price, can already be derived directly manually.

For systems of high complexity or complex control requirements, the methodology shall also indicate when operation cannot be satisfactorily tuned using a rule-based approach and when it is worth the effort to implement more advanced control strategies, such as MPC.

In further investigations a comparison to conventional RBC and more advanced MPC approaches will be made to demonstrate which of the optimization potentials can already be achieved by an optimized RBC and for which problems more complex controls like MPC are necessary to achieve a satisfying operation.

The influence of the model accuracy of the underlying optimization model on the extracted rules needs to be investigated in more detail. Further studies should show which temporal resolution and properties of the plants i.e. constraints in the optimization model are important for the rule extraction. Provided that the method already delivers satisfactory results for rule-based operation in generic design optimization procedures with lower model accuracy and temporal resolution, this would significantly improve the transferability of the methodology.

In addition, follow-up studies will show whether the accuracy achieved in rule extraction procedures such as clustering or decision tree classification already allows conclusions to be drawn about the performance of the control in reality, or whether it needs to be validated in general.

7. Acknowledgments

We gratefully acknowledge the financial support provided by the BMWK (The Federal Ministry for Economic Affairs and Climate Action), promotional reference 03SBE006A.

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