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Energy system optimization towards a fossil-free power plant portfolio

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Abstract:

To decarbonize our energy system, appropriate technology options must be established and applied at the right site. The investment decisions required for this are usually conducted based on techno-economic portfolio optimization. The presented research aims to optimize an energy system configuration for a district heating network of a global city located in Central Europe. The objective is to evaluate different configurations and determine the optimal combination for a fossil-free supply system. The energy system model is based on real district heating network data, including hydraulic restrictions, combined heat and power plants, heat-only boilers, heat storage, power-to-heat technologies, and fuel input options. Time series are heat demand, weather conditions, and exchange prices. Furthermore, investment costs and operating and maintenance costs are taken into account. Aristopy, a free and open-source Python-based framework, has been used to implement mixed-integer linear programming, which is solved by the state-of-the-art algorithm Gurobi. The model includes a time series aggregation to achieve accuracy and appropriate computation time. Multiple scenarios with different input data evaluate the robustness of each configuration. By assessing these configurations, the optimal system design is selected. The model succeeded in determining an optimal portfolio configuration and its operation. Simplification through time series aggregation has shown that the computation time can be shortened while providing the necessary accuracy. The scenario analysis shows the impact of the different input parameters and assumptions on portfolio planning. The presented methodology improves portfolio planning and operation of a real-world energy system. Simultaneously, license costs can be saved.

Keywords:

Energy System, Optimization, Decarbonization, District Heating, Python-Based Framework, Time Series Aggregation, Portfolio Planning, Fossil-Free, Renewable Energy

1. Introduction

The uncertainty and volatility of energy prices and fuel supplies have increased dramatically in recent developments within the energy market. This dynamic progress is also reflected in recent political and societal developments. The regulatory framework is an additional driver which impacts the operation and investments of power and heat generation units. The importance of scenario analysis is increasing due to the additional uncertainty. Optimization models are needed to find robust portfolios and analyze the impact of specific parameters. Within the presented research, the city, the district heating system, and the generation units under investigation are called by anonymous names.

In general, there are numerous research papers on energy system analysis, both on the level of methodological development and on the level of application-oriented research. Due to many works, only a relevant selection of overviews of the current state of research is compiled. DeCarolis et al. [1] conduct an extensive literature review to formalize best energy system optimization modeling practices. Kotzur et al. [2] note that many complexity drivers could be avoided a priori with a tailored model design. They review systematic complexity reduction methods for energy system optimization models and develop a guide for system modelers encountering computational limitations. Wirtz et al. [3] perform a comparison of different combinations of energy system model features: Piece-wise linear investment curves, multiple component resolution, minimum part-load limitations, part-load efficiencies, and start-up costs.

Decomposition approaches and approaches for optimization under uncertainty have also been proposed recently for energy system modeling. Wirtz et al. [4] present a Dantzig–Wolfe approach to decompose a mixed-integer linear program into multiple subproblems and a master problem. A realistic case study based on a district heating system was considered. They demonstrated that the proposed decomposition approach yields the same results attained by the original, not decomposed problem while achieving gains in scalability and computational times. Göke et al. [5] applied Benders decomposition to two-stage stochastic problems for energy planning with

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multiple climatic years. With their approach they slightly increase solve time of the master-problem, but greatly reduce the number of iterations. Yue et al. [6] have identified four prevailing uncertainty approaches applied to energy system optimization models: Monte Carlo analysis, stochastic programming, robust optimization, and modeling to generate alternatives. They provided a critical appraisal of the use of these methods.

Studies focusing on the local district heating portfolio and dispatch optimization were published in the past. Jüdes et al. [7] and Christidis et al. [8] investigated the contribution of heat storage for the district heating network using large-scale optimization models developed and solved within the General Algebraic Modeling System (GAMS). The advantage of pressurized short-term heat storage for operating a district heating network was investigated by Hofmann et al. [9]. Gonzalez-Salazar et al. [10] present a district heating network portfolio optimization. Due to computation time restrictions, they use a merit order model instead of mixed-integer linear programming. Concerning the local portfolio of the city under investigation, it is clear that comprehensive portfolio analyses require further methodological development in model reduction while maintaining the same quality of results.

This research analyzes the energy system's behavior depending on the changing energy market scenarios. The purpose is to find a suitable optimization method with an appropriate computational load and framework to analyze different scenarios concerning the district heating grid and the future portfolio. Based on different input scenarios, portfolio options are presented, which can support investment planning.

The article is structured as follows: The next section summarizes the methods and tools applied here. The system analysis presents the technology options, input data, and boundary conditions taken into account. The portfolio optimization and sensitivity analysis results are discussed in Section 4., followed by the conclusions.

2. Methodology

2.1. Energy System Optimization

The current energy market is more volatile than ever, and the urge to transform the current energy system into a more climate-friendly portfolio is at its highest peak. Due to these reasons, it has become even more difficult for most energy suppliers to determine the future energy system configuration that fulfills economic and environmental objectives. Energy system optimization is an essential tool to address this challenge.

There are various approaches for energy system optimization depending on the question to be answered within the decision process. In all cases, the goal is to determine a set of decision variables so that the value of the objective function is maximized or minimized while fulfilling all constraints. The optimization objective can be the dispatch of individual generation units or a system configuration optimization where the entire grid is considered over the given period.

An overview of the available functionality and the specific advantages and disadvantages of the energy system modeling frameworks and open models are presented on the websites of the Open Energy Platform [11] or the Openmod Initiative [12]. Both platforms aim to actively exchange and initiate relevant energy system modeling topics, approaches, and data. Since the field of the energy system modeling is broadly diversified, and each tool has individual strengths and weaknesses, the community helps to enhance the quality and efficiency. In addition to those platforms, Groissböck [13] presents a general assessment of open-source energy system modeling.

This research uses the Python-based, objective-oriented framework Aristopy, which was developed under the research project "MINLP-Optimization of Design and Operation of Complex Energy Systems" and is presented in the following section.

2.2. Aristopy

Aristopy[1] is a free and open-source Python-based framework for the optimization of energy systems. In contrast to other frameworks, aristopy allows integrated time series aggregation methods that can be used directly within the model, see section 2.3. Aristopy uses the algebraic modeling language of Pyomo [14, 15]. The user can formulate individual restrictions and constraint which adapts to multiple programs such as LP, MILP, or MINLP. Various solvers can be utilized. For this research, the optimization problem has been solved using Gurobi [16]. For visualization of results, aristopy uses Plotter[2].

In aristopy, an optimization model is set up by creating the class EnergySystem. Within the class, five pre-defined components (Source, Sink, Conversion, Bus, Storage) can be used to describe different characteristics and behaviors of the energy system parts. All inputs and outputs of components are connected with a class Flow, which contains all variables and ensures energy transport. Figure 1 shows a simple illustration of an example energy system and the dependency of each component.

The Source component contains only one output, which provides fuel in the example. With the help of a Flow component, the fuel is transported to the Conversion component, where fuel is converted into thermal and

[1] https://aristopy.readthedocs.io/en/latest/
[2] https://pypi.org/project/plotter/

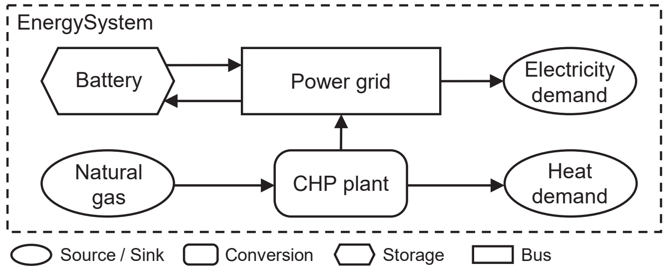

Figure 1: Simple example of generic model building using the class EnergySystem and the elementary component classes Source, Sink, Conversion, Bus, and Storage in the Python library aristopy. Translated adoption with permission from [17].

electrical energy. The energy flows are transported to a Bus component, where different streams of the same energy are gathered and transported to a Sink component. The Sink component, e.g., heat demand in the example, is the inverted component of Source. A Storage component (either battery or heat storage) can be added to the energy system, allowing more system flexibility. The storage can be directly integrated into the overall system or an individual grid by creating multiple Bus components.

Aristopy contains a particular class of photovoltaic or solar thermal collectors. An existing method from the Python library pvlib [18] is used for this. Furthermore, the built-in functions of add_variable, add_constraint, and add_objective_function_contribution are provided to add additional variables, constraints, and objective functions to the optimization model.

2.3. Time Series Aggregation

One of the biggest hurdles for an energy system optimization is the need to optimize numerous scenarios of possible future developments and the needed calculation time or computational capacity. Time series aggregation methods have been introduced for energy system optimization to reduce model complexity. Reviews are presented by Hoffmann et al. [19] and Teichgräber et al. [20]. This thesis uses the Python-based Time Series Aggregation Module (tsam) [21].

The concept of time series aggregation is to reduce an extensive and detailed data set into a representation with fewer time steps, ideally without loss of information by aggregating repetitive patterns. An appropriate method can reduce CPU and RAM requirements and make processing and analyzing extensive time series data sets efficient.

There are several time series aggregation methods. The most common is reducing the resolution by grouping the data into larger time intervals, from hourly time steps to days, weeks, or months. This method is called downsampling, which usually leads to underestimating the original times series' variances and the maximum and minimum values.

Besides the downsampling method, there is the segmentation method. It is a more complex but accurate method of aggregating time steps with similar characteristics to create an artificial time series replicating the original times series. There are different aggregation methods with their advantages and disadvantages. When this approach was introduced for energy system optimization, the heuristic method, where one representative day per month is selected, was a standard application. In the meantime, systematic aggregation methods are introduced, in which the time series is divided into particular periods of defined length and assigned to a cluster based on their similarity. The Euclidean distance function, see Eq. (1), is used to measure similarity. The equation is formulated for a one-dimensional distance where p and q represent two points on the real line.

$$d(p,q) = |p - q| \tag{1}$$

Three main methods exist to aggregate time series into groups with a single representative period. The most commonly used clustering method is the k-means algorithm. It belongs to the family of non-hierarchical cluster analysis methods where k random centroids are created in the feature space. All data points are assigned to the nearest centroid using the Euclidean distance function, which provides an initial cluster solution. Every data point is attached to one cluster, and the centroids are updated by finding the empirical mean of the features across all data points attached to that cluster. When the centroids are updated, the algorithm repeats the assignment of each data point to the next nearest (updated) centroid. The critical feature of a k-means algorithm is that the final centroids are not actual data points but a calculated mean of data points within that cluster.

Another algorithm called k-medoids chooses the final centroids from the actual data points, thereby allowing for greater interpretability of the cluster centers than in k-means. The "Partitioning Around Medoids" (PAM)

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algorithm finalizes the point as a new centroid from the existing data points with a minimum loss. Besides k-means and k-medoid, there is the hierarchical clustering algorithm. In hierarchical clustering, each data point is grouped into a cluster tree by treating all data points as a separate cluster. When all data points are determined as individual clusters, the algorithm identifies two clusters that are closest together. Those two clusters will be merged into one cluster. As a result of this iterative process, all clusters are merged.

Since peak periods are not representative of a whole group or cluster of periods, the methods introduced for time series aggregation have the disadvantage of potentially cutting off so-called peak periods. An accurate energy system design must be able to meet all requirements. There are different approaches for identifying and mapping the extreme points. The append method adds the extreme periods as additional representative periods to the other representative periods. In contrast, the additional-cluster-center method sets the peak period as an additional new cluster center. The replace-representative-period method integrates the extreme value where the peak period is assigned as the new representative of the cluster.

For the analysis, it is essential to set the correct number of representative data points the user gives. Depending on the number of representative data points, the results can differ. Additionally, choosing the period length and the number of time steps per representative period is essential for the time series aggregation. Different energy systems behave individually depending on the preset of representative clusters. Usually, the aggregated time series are modeled individually, where the connection and correlation between those periods are not modeled accordingly. It can impact the integrated storage system, so it is suggested to choose more extended periods to model the impact of storage.

3. System Analysis

Figure 2 represents the example energy system generated for this research. The considered optimization problem represents an energy system where the coal capacities have been phased-out. By taking out the coal-firing capacities and providing each production site with various potential technology options, the solver can optimize the optimal portfolio configuration for the system and each production site.

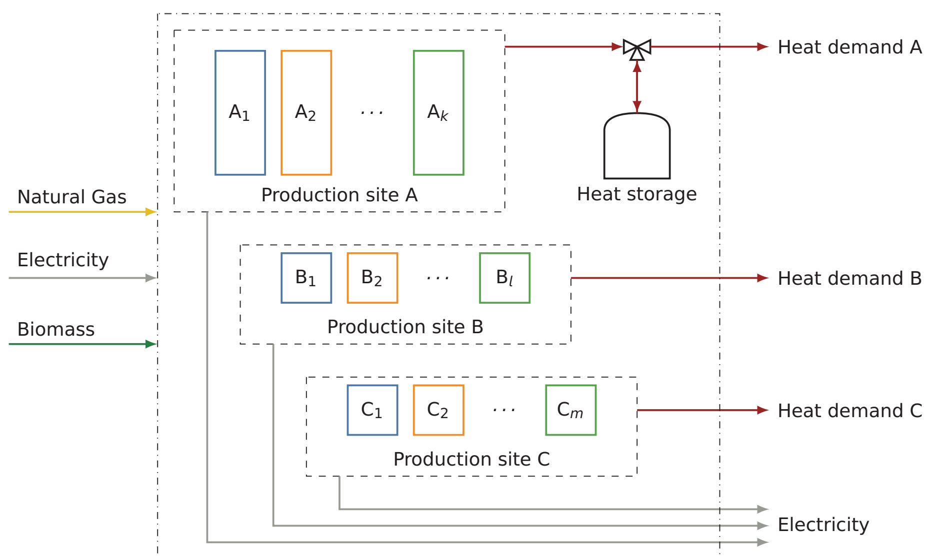

Figure 2: Simplified district heating system. Colors indicating recent and potential technology options at the sites.

As Figure 2 shows, the model is given with the possible fuel inputs, potential technology options, and the heat demand which must be met for each time step. The model considers portfolio options under various scenarios to find the most suitable and beneficial technology option for each site. The electrical grid is not given as a demand but as a market where the generation units can either sell or buy. The district heating grid can be divided into multiple sub-grids considering the geographical condition. Each generation site is assigned to a specific sub-grid to avoid significant heat losses and bottlenecks. The possibility of transferring heat from one sub-grid to nearby sub-grids is also modeled. Even though, it is physically possible to transport to the furthest sub-gird, it is very unusual considering the grid efficiency. Even when primary capacity fails, the heat-reserve boilers compensate for the capacity instead of transporting it from other sub-grids. The heat-reserve boilers are not set as a variable in this thesis but as given plants with extremely high operating costs.

The objective for the optimization is to maximize the net present value (NPV), see Eq. (2). The net present value measures the financial profitability of the portfolio. Equation (2) determines the difference between all revenues and expenses over the economic life of the investment.

$$\max NPV = -I + S + C \cdot k^{\mathrm{AF}} \tag{2}$$

In this equation, all expenses and revenues arising from the investment are discounted throughout the investment. As part of the input assumptions, various model parameters have been pre-determined.

All technology options are modeled with a fuel equation with technology-specific coefficients k_i and time-depending variables (Fuel rate $\dot{F}$, Electric power $\dot{W}_{\mathrm{el}}$, and heat rate $\dot{Q}_{\mathrm{th}}$); and if necessary (combined technology) with an additional $\dot{W}_{\mathrm{el}}$, $\dot{Q}_{\mathrm{th}}$-function.

$$\dot{F}_{\mathrm{f}} = \begin{cases} k_1 \cdot \dot{Q}_{\mathrm{th}} & \text{Heat pumps or heat-only boilers, } f = \{\text{Electricity, Bioenergy, } \mathrm{CH_4}\} \\ (k_1 + k_2)^{-1} \left(\dot{W}_{\mathrm{el}} + \dot{Q}_{\mathrm{th}}\right) & \text{Gas turbines w/ or w/o heat-recovery boiler, } f = \{\mathrm{CH_4}, \mathrm{H_2}\} \\ k_1 \left(\dot{W}_{\mathrm{el}} + k_2 \cdot \dot{Q}_{\mathrm{th}}\right) + k_3 \cdot Y & \text{Combined heat and power plants, } f = \{\mathrm{CH_4}, \mathrm{H_2}\} \text{ and } Y = \{0, 1\} \end{cases} \tag{3}$$

Fundamental model parameters are given in Table 1. The complete model with all equations and specifications can be obtained from the authors. Note that due to corporate confidentiality, actual values can not be given.

Table 1: Fundamental model parameters and maximum heat rate per unit of the technology options

Parameter	Symbol	Unit	Value
Number of production sites	N	[–]	5
Economic lifetime	t	a	15
Future technology options (Abbreviation)	$\dot{Q}_{\max}$ [MW]		
Natural gas heat-only boiler (GHOB)	40		
Combined cycle gas turbine (CCGT)	230		
Gas turbine (GT)	120		
Bioenergy heat-only boiler (BIOB)	100		
River heat pump (HP)	50		
Geothermal heat pump (GEOT)	50		
E-Boiler (EB)	40		

4. Results

4.1. Portfolio Optimization with time aggregation

As mentioned in the previous section, the total solution time increases with the additional complexity of the optimization problem. However, it is essential to analyze various scenarios with different assumptions to find the most robust portfolio for the future. With an average optimization duration of 5 to 6 hours for an optimization period of 15 years, the effort to investigate and analyze multiple scenarios is too high. The time series aggregation algorithm has been implemented to simplify this process and aim for similar results. For the analysis, different types of algorithms were used to analyze the impact of the aggregation methods. For the consistency of the result analysis, a similar scenario has been selected to compare different algorithms.

First, multiple combinations of representative periods and period lengths have been analyzed. Table 2 shows the average configuration variance with different representative periods and period lengths. The variance represents the percent difference compared to the original scenario result, optimized with hourly input data. The first column, Cluster Period, represents the combination selected for the optimization. The first number indicates the number of representative periods from the input data of 15 years and hourly resolution. The second number indicates the length of each period, represented as hours in full resolution. For the analysis, 18 representative periods and length variations have been optimized with the k-mean algorithm. The variance from the reference scenario has been filtered after technology types. As assumed, the number of representative periods and the length of the period drives the total solution time. The longer the period, the more optimized time steps, which leads to a longer solution time. Table 2 also shows that each technology option behaves differently depending on the variation of the cluster period. A significant variance can be seen for the gas heat-boiler option. The gas boilers have been utilized in the full hourly resolution, especially for peak shaving. By aggregating the time series, those continuous peaks of the heat demands have been relatively neglected, which makes the investment in gas boilers unnecessary. The analysis of the hourly resolution result is that the operation periods

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of gas boilers are limited, but it is still economical to have the gas boiler as peak demand cover when the electricity generation is not beneficial for the operator.

Compared to the heat-only generation, the co-generation units show relatively low variance. Even though the solver could invest in the GT, which is also an option, the preferred investment is the CCGT technology. The CCGT has the lowest variance since the flexibility of such technology is higher and adaptable for almost any input assumptions. In the hourly resolution result of the original scenario, bio boilers were not preferred since the period where the bioenergy is more favorable compared to other technology options was significantly low. This relativity is underestimated by aggregating the time series, which leads to the solver investing in bioenergy-based heat generation units. Similar to the solution time, the impact of the number of periods and period lengths for the P2H technology is undoubtedly visible. Since the P2H technology is strongly dependent on the EEX price, which varies hourly in this energy system, the impact is significant. The more time steps are considered in the energy system, the more the error of over-investing or under-investing in P2H technology will decrease. As the analysis shows, the suitable representative periods are between 12 and 18 days concerning the accuracy of the configuration and the optimization duration. For the length of the period, the length of between 24 and 72-time steps is enough to expect a sufficient optimization result.

Table 2: Variance per technology and solve time for different representative periods and period lengths

Cluster Period	GHOB [%]	CCGT [%]	GT [%]	BIOB [%]	HP [%]	GEOT [%]	EB [%]	Solve time [s]
4_24	−179.38	14.46	9.79	3.91	25	0	73	7
4_72	−142.55	4.95	56.68	0	25	0	73.17	8
4_168	−136.92	0	61.52	0	25	0	61.3	16
8_24	−178.73	15.62	39.22	35.52	25	0	72.5	9
8_72	−172.38	0.18	34.23	0	25.34	0	71.67	16
8_168	−165.68	0	62.37	19.67	25	0	63.6	30
12_24	−187.73	6.85	75	55.86	25	0	72.48	11
12_72	−178.11	0	60	21.52	25	0	65.12	24
12_168	−178.1	0	42.41	8.85	25	0	52.57	39
18_24	−182.1	0	58.8	20	0.65	0	27.93	15
18_72	−188.88	0	71.03	22.23	5.76	0	65.57	30
18_168	−175.25	0	54.73	24.32	25	0	50.25	67
24_24	−250.28	0	64.37	23.37	3.43	0	44.16	18
24_72	−192.95	0	69.45	25.05	5.05	0	66.92	44
24_168	−178.40	0	50.72	21.91	12.33	0	50	91
72_24	−158.05	0	48.21	0	1.46	0	19.83	53
72_72	−165.93	0	57.52	19	2.09	0	27.31	114
72_168	−172.96	0	42.84	7.04	5.782	0	32.12	397

The results also showed that the capacitive variance differs depending on the technology and fuel type, but it still proves that the behaviors of the overall configuration are complementary. Interestingly, the natural gas-based technologies were relatively over or underestimated, even up to 100% underestimation. The overestimation and underestimation of different technologies also highly depended on the input scenarios, emphasizing the importance of input assumptions. The time series aggregation fulfills its requirement to assess numerous scenarios and various input assumptions. It is essential to acknowledge that optimization results for future configuration planning should be assessed in comparison and not as a stand-alone result. Due to the highly unpredictable and incalculable forecast data, the optimization serves the purpose of observing different behaviors of the technology, which can support a robust portfolio configuration.

Figure 3 compares *NPV* and *CAPEX* results for different time series aggregation algorithms. The k-medoids aggregation algorithm is excluded from this analysis due to the high aggregation time and computational load. With the given input assumptions, the solver could not build and aggregate the time series of 15 years with the k-medoids algorithms. However, the following section includes the k-medoids algorithm for shorter time series. As expected, the averaging algorithm is the most distanced result from the reference scenario. The relativeness of different input assumptions is neglected by averaging 140 256 time series into dramatically lower resolution, making the result not comparable with the reference scenario.

Figure 4 shows the variance of each aggregated optimization result filtered by technology options. Like the financial result, the k-medoids algorithm demonstrates each technology's least capacitive difference. It is

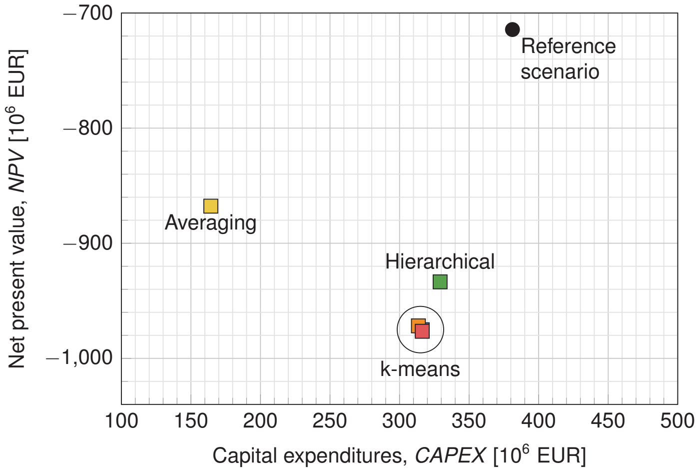

Figure 3: Net present value and capital expenditures for different time series aggregation methods

recognizable that the averaging method overestimates the capacities for each technology option and that the hierarchical method underestimates the capacity of heat pump technologies. The hierarchical algorithm ranked the heat pump technology lower than the other algorithms and assessed the gas turbine higher. The simplification of the input assumptions by the hierarchical algorithm is stronger than the other algorithms. Technologies with volatile dependencies can be underestimated in this algorithm, which makes it more difficult for technologies such as heat pumps or E-boilers to set the suitable representative period due to more unexpected developments. The capacitative overestimated technology options directly or indirectly depend on the most volatile input assumption. Even though the input energy of a geothermal plant depends on the power price, the constant heat source can level out the difference, elevating the value as a promising technology. The difficulty to optimize and the most discrepancy are shown for the gas-fired heat-only-boilers dispatched for the peak shaving. The number of representative periods is insufficient to express each peak demand, leading to higher variance in the GHOB result.

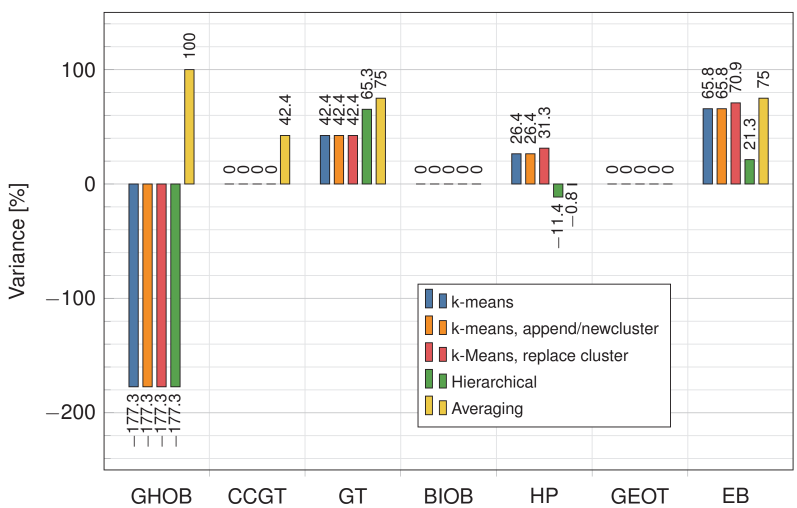

Figure 4: Variance comparison by cluster algorithm and capacity of technology

Overall, using the k-means or hierarchical algorithm as a clustering method is favorable for reducing the optimization problem's computational load. Keeping in mind that depending on the algorithm and the technology option, the particular capacitative result might be overestimated or underestimated. To reduce the computational load and shorten the optimization duration, the time series aggregation methods with appropriate periods can give sufficient indications for each portfolio configuration.

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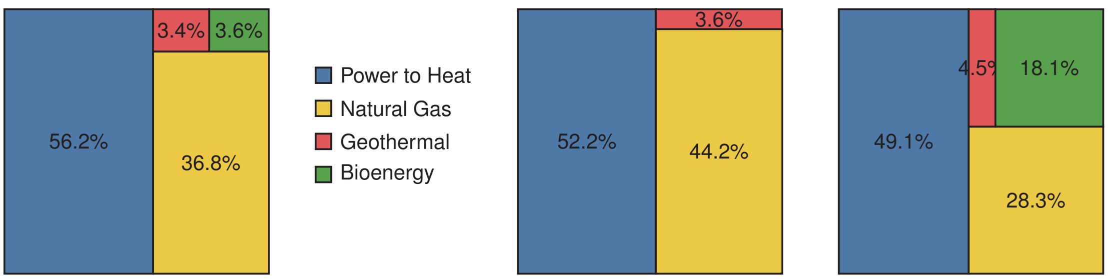
4.2. Sensitivity Analysis

Multiple activities exist to decarbonize gas-based power plants to realize a continuous hydrogen supply in the current gas grid. With enough supply for the required sectors, hydrogen will be the fastest way to decarbonize the gas-fired processes in Germany. Considering the significant increase of renewables in power generation, the potential of inland green hydrogen is considerable. This sensitivity analysis assumes that there will be enough hydrogen from 2040 onwards for the energy sector in Germany. Furthermore, green hydrogen combustion is counted as fossil-free fuel input, excluding the CO_2 certificate fee. For this analysis, the gas price ends in 2040 and is replaced by the hydrogen price from 2040 onwards. It assumes that there will be no natural gas in the grid from 2040, and the existing grid will be operated 100% with hydrogen. Besides the hydrogen price, all other input assumptions are equal to the original scenarios.

Figures 5a and 5b show the fuel mix of the portfolio for the H_2-integrated scenario and the original scenario. The apparent difference is the investment in bio boiler in the hydrogen integrated scenario. The share of gas/H_2-plants decreased, and the additional bio boiler and P2H plant compensated for the gap. The significant decrease in gas/H_2-based heat generation is recognizable from 2040. Due to the amortization of a plant, the bio boiler is invested from the beginning of the period. However, the high hydrogen price compensation can be seen by the increased heat generation of P2H and bio boiler from 2040. Even though hydrogen combustion relieves the CO_2 certificate fee, the hydrogen price is still too high to compete against power-based or bio-energy-based technologies.



(a) H_2-integrated reference case

(b) Reference case

(c) H_2-integrated reference case (hiearchical aggregation)

Figure 5: Scenario results showing fuel mix

Figure 5c shows the H_2 sensitivity analysis results compared to the aggregated results. As a result of the main portfolio optimization, the hierarchical algorithm was chosen for the sensitivity analysis. The results represent a higher variance of bioenergy and P2H share of total installed capacities. The higher flexibility of P2H technologies is preferable when the depths of the EEX price development are low. Increasing gas prices and switch to expensive hydrogen prices encourages the model for more investment in P2H technologies, and the increase in the CO_2 price also encourages investment in bio boilers despite the higher investment costs. Especially the discrepancy in bioenergy share is higher than in other fuel types. The main reason behind this result is the transition from natural gas to hydrogen. The non-aggregated scenario considers the yearly development and transition of fuel switch, making the natural gas capacities very attractive before the transition. However, the aggregated scenario emphasizes the higher price of hydrogen in the later years, which reduces the natural gas / H2-based assets and increases the alternatives.

5. Conclusion

Within this contribution, a simplified district heating system has been modeled as a case study with the Python-based optimization framework aristopy. The objective was to optimize the future district heating portfolio configuration and assess various impact parameters influencing the composition and operation of the portfolio. Additionally, the work analyzes the impact of the time series aggregation methods on portfolio planning to simplify and accelerate the comparison of different scenarios.

Potential technologies were analyzed to close the capacitative gap resulting from the coal phase-out. The existing district heating systems and recently commissioned power plants have been modeled with the optimization framework aristopy. Different technology options were implemented for each generation site for the future scenario comparison, considering the geographical and technological feasibility. The model identifies the main drivers for an advantageous portfolio configuration by comparing various scenarios with different input assumptions.

This contribution also showed that the right time series aggregation method could reduce the computational load and produce viable optimization results for portfolio planning. From the total optimization time of 3 to 8 hours for 15 years of considered time horizons, the time series aggregation could reduce the time to under 60 seconds with manageable optimization results. Comparing different clustering algorithms and representative periods, the hierarchical algorithm showed the most promising optimization results with a significantly shorter solution time. For clustering time series of 15 years, 12 to 18 representative periods with 24 period lengths were sufficient to indicate the configuration well.

An improvement potential is the time determination of the investment or refurbishment. The decommissioning process of existing coal-fired power plants is a long-term process, and decommissioning or refurbishing existing gas units into H_2-firing plants will also take time. By integrating the time factor as a variable for the investment, the optimized time for the construction and commissioning phase can be estimated considering the transformation plan of the portfolio. In addition to the time determination, various factors, such as government support schemes, change with a fixed factor over time. These factors are primarily key factors derived from the regulatory framework. Certain subsidies are given by the full-load operation hours, or efficiency goals reached every year. By aggregating the input assumptions, it is impossible to consider such subsidy types and goals, which depend on the generation unit's operation. Such considerations can improve portfolio planning but require detailed and accurate forecast data. The value of such optimization can be enhanced by integrating multi-objective or multicriteria optimization of an energy system. With more ambitious climate goals, the regulations for the energy sector will be stricter and more demanding. This means the government will require specific key indicators from the energy utilities. Key indicators such as primary energy factor, yearly renewable share in the system, or specific greenhouse gas emissions can influence the dispatch of each generation unit. The current aristopy framework allows the user to adjust the objective function, but each optimization problem must have only one objective function. By integrating multi-objective optimization, the user can plan a portfolio configuration that satisfies different regulatory requirements and maximizes the financial value of the portfolio. The downside of such optimization is the computational load. A multi-objective optimization comes with an exponentially higher computational load and solution time due to the multidimensional variables. However, when comparing various scenarios and the impact of the input assumptions, the additional computational load could be compensated by various methods, such as time series aggregation. When multi-objective optimization with an appropriate solution time and assessable granularity is possible, it can enormously enhance the planning of a portfolio configuration.

CRediT author statement

Duk Yong Kwon: Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Writing - Review & Editing **Mathias Hofmann:** Conceptualization, Methodology, Validation, Resources, Writing - Original Draft, Writing - Review & Editing, Visualization, Supervision

Nomenclature

Abbreviations

BIOB Bioenergy heat-only-boiler

CCGT Combined cycle gas turbine

CHP Combined heat and power

CPU Central processing unit

EB E-Boiler

EEX European Energy Exchange

GAMS General Algebraic Modeling System

GEOT Geothermal heat pump

GHOB Natural gas heat-only-boiler

GT Gas turbine

HP River heat pump

LP Linear programming

MILP Mixed-integer linear programming

MINLP Mixed-integer nonlinear programming

P2H Power-to-heat

RAM Random-access memory

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Letter symbols

C Costs, €

$CAPEX$ Capital expenditure, €

d Euclidean distance function, –

$\dot{F}$ Fuel rate, MW

I Investment, €

k Present value of annuity factor, –

k_i Technology specific coefficient, –

NPV Net present value, €

p Point p ,–

q Point q, –

$\dot{Q}$ Heat rate, MW

S Subsidy, €

t Economic lifetime, a

$\dot{W}$ Work rate, MW

Y Binary variable, –

Subscripts and superscripts

el Electric

f Fuel type

max Maximum

th Thermal

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