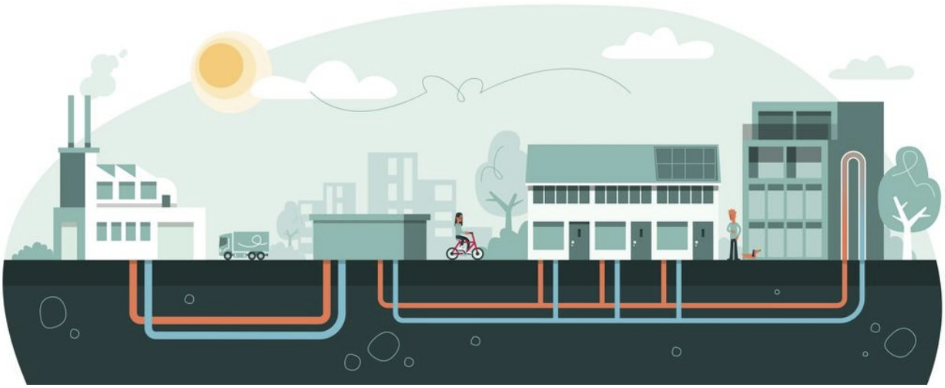
A systems engineering approach to optimisation in hybrid renewable energy systems

Optimising asset capacities for Eneco's district heating network in Utrecht



A SYSTEMS ENGINEERING APPROACH TO OPTIMISATION IN HYBRID RENEWABLE ENERGY SYSTEMS

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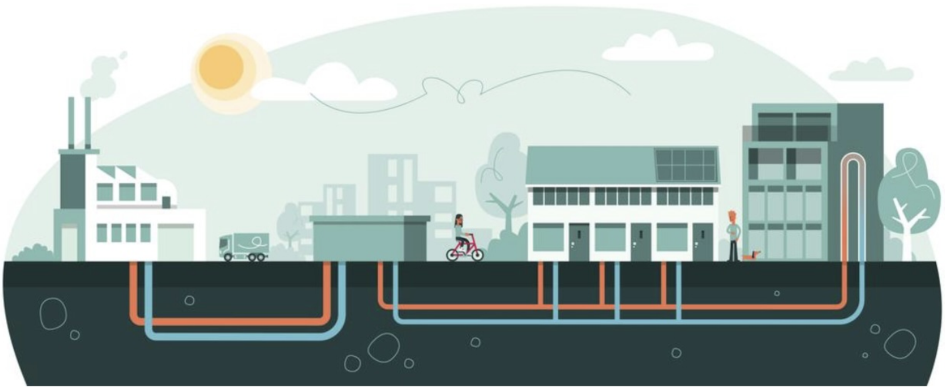

Dissertation

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Abstract

With the pressing need to address climate change and reduce greenhouse gas emissions, governments around the world have set ambitious climate goals, necessitating a transition to renewable energy sources. In the Netherlands specifically, the government has recognized the potential of district heating networks as a vital strategy for decarbonization, given that 81.5% of domestic energy consumption is dedicated to thermal loads. The development of new energy assets, the integration of storage solutions, the use of intermittent renewable energy sources, and the inclusion of multiple energy carriers such as fuels, power, and heat, collectively referred to as hybrid renewable energy systems, have made the energy infrastructure more complex than ever before. The challenge lies in understanding the implications of integrating diverse renewable assets and optimizing the system for both reliability and economic feasibility, as optimal sizing in hybrid renewable energy systems remains insufficiently understood.

This study aims to answer the following research question: What is an effective approach to capacity optimisation in renewable energy systems that integrate thermal and power sources with hybrid energy storage?

This study adopts both qualitative and quantitative research approaches, employing multi-actor analysis, system design, optimization techniques, and data analysis to determine the optimal sizing of the identified system components. The study integrates real-world data from Eneco's district heating network in Utrecht, employing optimisation models to minimise costs while ensuring a reliable supply of heat for the connected households. The research addresses sub-questions related to optimisation techniques, hybrid system design, and operational performance.

The study results show that a systems engineering approach to capacity optimization in hybrid renewable energy systems can provide robust solutions to the challenges of balancing reliability, economic feasibility, and sustainability in energy infrastructure. By taking an integrated approach that spans multi-actor analysis, system design, optimization design, model development, and result analysis, relevant system components can not only be identified but also capacity-optimized. Throughout the study we have shown that single-layer optimisation using mixed integer linear programming provides the most accurate results in diverse hybrid systems with complex asset dispatch. Furthermore, we identified masked time resolution adjustment as the highest-performing simplification technique, achieving a 91.58% reduction in solution time while showing minimal differences in results compared to full optimization. For Utrecht's district heating network specifically, we showed that a renewable hybrid system, relying on thermal energy storage, power-to-heat, and CO_2 compensated fuel-to-heat, is economically and technically feasible up until an operational power-to-heat fraction of 85%.

Executive summary

The study results show that a systems engineering approach to capacity optimization in hybrid renewable energy systems can provide robust solutions to the challenges of balancing reliability, economic feasibility, and sustainability in energy infrastructure. By taking an integrated approach that spans multi-actor analysis, system design, optimization design, model development, and result analysis, relevant system components for Eneco's district heating network in Utrecht have been identified and capacity-optimised.

The multi-actor analysis reveals that Energy Production Utrecht (EPU) operates within a highly complex decision-making environment influenced by high-power stakeholders, including the municipality, local community, and grid operators. The most significant dependency is between EPU and grid operators. Due to ongoing decarbonization efforts, EPU is anticipated to rely more heavily on power-to-heat (P2H) in the future, necessitating larger grid connections throughout the city. The timing and method of P2H implementation will either alleviate or exacerbate grid congestion. By operating P2H assets during off-peak hours to generate heat, EPU can help alleviate grid congestion by storing thermal energy in short-term storage assets for use during peak thermal demand hours. This approach, in turn, reduces peak power demand. Conversely, if P2H assets are used during peak power demand hours, EPU risks contributing to grid congestion. To foster a mutually beneficial relationship, EPU and grid operators must maintain close communication to support each other's goals. Additionally, it's essential to recognize that persistent grid congestion has spurred new regulations, such as the ATR85/15 rule, which allows grid operators to restrict power supply up to 15% of the time.

Following the actor analysis, system analysis was used to identify the relevant system components. Currently, there are four thermal assets that can be integrated in EPU's district heating network: Combined Cycle Gas Turbines (CCGTs), peak boilers, Heat Pumps (HPs), and E-boilers. While alternative thermal sources such as waste heat, biomass, and geothermal have been evaluated, successful implementation of these assets has been shown to be unlikely for various reasons. Additionally, we evaluated multiple storage assets of which two have been included in the results: Tank Thermal Energy Storage (TTES), and Aquifer Thermal Energy Storage (ATES). TTES is primarily used to balance short term supply and demand and therefore used as a peak asset. ATES on the other hand is used for seasonal thermal energy storage due to its favourable efficiency and cost characteristics.

The optimisation design showed that for EPU, minimum cost emerges as the most important objective, constrained by emissions and reliability requirements. The optimisation makes use of mixed integer linear programming, a computationally expensive method that is guaranteed to find the global optimum. To alleviate some of the computational complexity, two simplification methods were applied to the model: k-means clustering and masked time resolution adjustment. Comparison of optimisation results show that masked time resolution adjustment yields the most accurate results while achieving a 91.58% reduction in solution time.

To assess the operational performance of the optimization results, we used simulation techniques to create a synthetic dataset comprising two years of hourly data. This synthetic dataset was generated based on probabilistic patterns observed in the 2023 thermal demand data. When evaluating the operational performance of the optimization results against the synthetic data, we found that none of the scenarios achieved the benchmark of a Loss of Heat Supply Probability (LHSP) of 0. Instead, LHSP averaged 0.041% across the scenarios. This discrepancy is due to higher peak demand in the synthetic dataset compared to the 2023 thermal demand used for system optimization. From this, we conclude that optimization alone does not provide sufficient capacity to handle periods of exceptionally high demand. Therefore, EPU should ensure the availability of additional peak capacity to maintain performance during unprecedented demand peaks. This redundancy would not only support operational reliability during demand peaks but also provide resilience during maintenance activities or asset failures.

From the research we can provide EPU with multiple strategic recommendations. The first insight is that, given the regulatory environment and ongoing challenges surrounding grid congestion, the implementation of a hybrid system design—relying on power-to-heat (P2H), fuel-to-heat (F2H), and fuel-to-power technologies—emerges as the most resilient and adaptable approach from a multi-actor perspective. The optimisation results show that such a hybrid approach must rely on heat pump capacity ranging from 50 MW_{th} to 132 MW_{th}, CCGT capacity ranging from 177 MW_e to 49 MW_e, and peak boiler capacity ranging from 32 MW_{th} to 54 MW_{th}. Additionally, EPU should incorporate thermal energy storage, including ATES with a capacity of 100 MW_{th} and a storage capacity between 64 GWh_{th} and 132 GWh_{th}, as well as TTES with a capacity ranging from 42 MW_{th} to 52 MW_{th} and a storage capacity between 259 MWh_{th} and 318 MWh_{th}.

Furthermore, we identified decentralised DHN operation as the most efficient application of results. By placing assets in secondary locations, thermal loss during transport is decreases, asset dispatch is simplified, and heat pump efficiency is increased. However, decentralised operation would limit the reach of thermal assets, only allowing them to supply heat to their specific network. It is currently unknown what locations have spatial availability and what the grid capacity is for those locations. Therefore, EPU should conduct further research into the placement of assets in secondary locations identifying what locations are suitable. An alternative approach that can capture many benefits of decentralized operation while limiting its drawbacks is lowering the temperature of the primary grid. This approach would also decrease thermal losses and increase the efficiency of heat pumps while allowing these assets to supply heat to all secondary networks. Furthermore, it would allow TTES assets to be placed in the primary grid, and allow ATES operation with a heat exchanger rather than a heat pump, decreasing system costs. However, a temperature reduction would also decrease grid capacity, as thermal demand is currently met through temperature regulation, potentially requiring additional peak assets in secondary locations. Therefore, it is essential for EPU to conduct further research into the possibilities of temperature decrease.

Finally, the results show that affordable and efficient seasonal thermal energy storage plays a critical role in the success of district heating networks. Therefore, EPU should initiate a pilot project for the implementation of seasonal storage using ATES.

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1 Introduction

As the world rapidly experiences the consequences of climate change, Eneco has committed to an ambitious mission of "green energy for everyone" by accelerating the energy transition and achieving complete climate neutrality by 2035 (Eneco, 2024f). This accelerated transition has brought renewable energy sources (RES) into the spotlight. However, despite renewable energy prices being cheaper than energy from fossil fuels, as measured by the levelized cost of energy (LCOE), their variable nature poses challenges for maintaining a balanced grid (IRENA, 2023). In 2023, grid imbalances caused electricity prices to be negative for a total of 316 hours, highlighting the challenges posed by renewable sources and the need for effective integration strategies (Harreman, 2023).

Given the intermittent and volatile nature of RES, the focus within integrated renewable systems has shifted significantly toward the role of energy storage. (Huang et al., 2024). Energy storage systems (ESS) can absorb energy during periods of surplus generation and subsequently release it when demand exceeds supply. This smooths the randomness of renewable energy, reduces curtailment, and the need for backup systems to meet peaks in demand (Wang et al., 2022). Each storage technology offers distinct advantages and challenges, influenced by factors like round-trip efficiency and energy density (Huang et al., 2024). Storage systems must be capital efficient, energy efficient and reliable. Currently, most energy storage solutions struggle to address multiple requirements at once (M. Liu et al., 2023). Therefore, implementing a variety of storage systems in a hybrid approach enhances system flexibility and economy by balancing out the shortcomings of each individual storage technology (Wang et al., 2022).

In the Netherlands, 81.5% of domestic energy consumption is dedicated to thermal loads, underscoring the importance of thermal energy in the Dutch energy infrastructure (Luteijn & Wetzels, 2023). Given the high thermal demand, district heating networks (DHNs) have become a crucial focal point for the Dutch energy transition and an integral part of the government's sustainability agenda. Recognizing their potential, the Dutch government aims to double the number of households connected to DHNs, targeting an additional 500,000 households by 2030 (Rijksoverheid, 2023). DHNs are not only more efficient, with 66% fewer emissions compared to domestic heating systems, but they also serve as a crucial sink for surplus electricity. DHNs that integrate thermal energy storage, known as district heating and storage networks (DHSNs), can store excess energy as thermal energy. This capability allows DHSNs to contribute to grid balance, absorbing both short-term and seasonal imbalances. Therefore, well-designed DHSNs that incorporate hybrid energy storage systems play a crucial role in both decarbonizing household energy demand and alleviating grid congestion.

Another advantage of DHSNs is that thermal energy storage (TES) is cheaper than battery energy storage (BES). While BES is effective, it is costly and depends on scarce resources, presenting both economic and environmental challenges (Li et al., 2023). Conversely, TES utilizes abundant, environmentally friendly materials and offers a more cost-effective solution. With capital costs between €0.1 and €20 per kWh, compared to €225 per kWh for BES, TES presents a more economical solution while aligning more with energy demand (Hauer et al., 2013; Huang et al., 2024). The ability to affordably store large amounts of energy allows DHSNs to significantly accelerate the energy transition by integrating district heating networks (DHN) and power grids, providing crucial flexibility. Electricity can be directly utilized to satisfy demand or converted into thermal energy to be directly used or stored. By simultaneously balancing power and thermal loads, DHSNs facilitate the widespread adoption of RES.

Recent research has shown that hybrid renewable energy systems, which integrate both BES and TES, have the potential to nearly increase capacity factors twofold while improving a range of economic indicators by 30%. (Hamilton et al., 2020). Integrating hybrid ESS improves economic performance by 13.4% and reduces CO_2 emissions by 24.6%, due to a 53.9% decrease in renewable energy curtailment. (Tooryan et al., 2020; Wang et al., 2022). Nonetheless, the reliance on a singular RES within a renewable energy system would demand an exceptional energy storage capacity, leading to high capital expenses. To address this challenge, integrating solar, wind, and other renewable electricity and heat sources could potentially reduce the need for storage and, consequently, lower overall system expenses. The sizing of system components can profoundly impact the overall economic performance and reliability of hybrid renewable energy systems. According to T. Liu et al., economic performance is commonly evaluated using the levelised cost of energy. On the other hand, system reliability is equally important, as highlighted by the emphasis on the loss of power supply probability (LPSP) in numerous studies (2022). Evaluating reliability requires simulation methods that create data using predefined probability distributions for unpredictable factors such as renewable energy generation and energy demand patterns (Zheng et al., 2018). Combined with a hybrid RES approach, leveraging the synergies between thermal and battery energy storage, could provide a valuable transition strategy towards an integrated hybrid energy system for Eneco (figure 1). However, the implications on hybrid system size and scalability, particularly regarding costly energy storage, and the total performance of the system remain insufficiently understood, warranting the adoption of an optimal system sizing approach.

1.1. BACKGROUND

Utrecht's district heating network plays a crucial role in the city's energy infrastructure, providing efficient and reliable heating to residential and commercial buildings. This chapter delves into the current state of this network, exploring its operational framework and the diverse energy sources it employs. As Utrecht navigates the energy transition, the integration of renewable energy sources has become increasingly significant. This shift not only aims to reduce greenhouse gas emissions but also to enhance energy security and sustainability. Additionally, the chapter examines the existing thermal energy storage solutions within the network, highlighting their role in balancing supply and demand, and ensuring a stable energy flow. By providing this comprehensive background, we lay the foundation for understanding the critical challenges and opportunities in optimizing Utrecht's district heating system for a greener future.

1.1.1. DISTRICT HEATING NETWORK

The district heating network (DHN) is a crucial component of modern urban infrastructure, providing efficient and centralized heating solutions to residential and commercial buildings. These networks are integral to government sustainability plans. By 2030, the Dutch government aims to connect an additional 500,000 residential buildings to DHNs. To support this goal, it has introduced a €150 million subsidy (Rijksoverheid, 2023).

Utrecht's district heating network, spanning 1,258 kilometers of piping, is one of the largest in the Netherlands (Nieuweweme & Hagenstein, 2024). It supplies roughly a quarter of the city's thermal energy demand, equivalent to 55,000 households, providing a more sustainable alternative to in-home central heating. This sustainability is largely due to the highly efficient power plants, achieving a 66% reduction in CO2 emissions compared to domestic systems (Eneco, 2022).

The DHN can be divided into two closed-loop systems: the primary network and the secondary network. In the primary network, water is heated using (waste) heat from one of Eneco's combined cycle gast turbines (CCGT). This network transports thermal energy in the form of hot water (minimum 90°C) from the power plants to a heat transfer station (WOS). Because the maximum flow of water volume is determined by the diameter of the pipes and the speed of the pumps, thermal demand is met through temperature regulation, raising the operating temperature during periods of high demand to a maximum of 120°C.

At the WOS, hot water enters a heat exchanger, transferring heat from the primary network to the secondary network. The cooled water leaves the WOS and circulates back to the power plant for another cycle. The secondary network transports the hot water (70°C - 90°C) from the WOS to residential buildings in Utrecht and Nieuwegein, where it flows through a heat exchanger to provide space heating or warm water. After which, the cooled water flows back to the WOS for another cycle (Figure 1.1). Eneco's DHN is divided into four districts: Nieuwegein, Leidsche Rijn, Overvecht, and Utrecht City, each containing one or more heat transfer stations.

1.1.2. THERMAL ENERGY SOURCES

While Eneco is working on improving the sustainability of their power and heat supply in Utrecht, at present the city relies heavily on fossil fuels. The two largest power

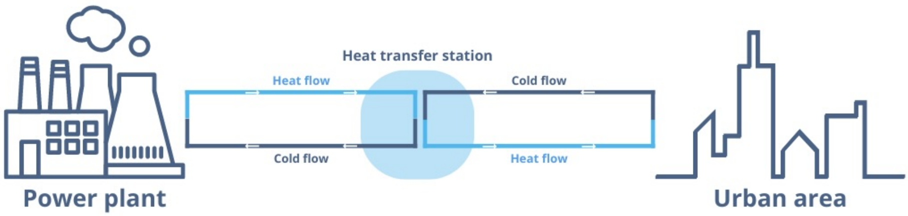

Figure 1.1: A schematic representation of the DHN with the primary and secondary network separated by a WOS

plants currently in operation are Lage weide 06 (LW06) and Merwedekanaal 12 (MK12) (Table 1.1). Both are CCGTs that produce electricity and heat simultaneously with a remarkably high efficiency of 85%. The high efficiency comes from utilizing what would otherwise be waste heat from the electricity generation process for district heating. In contrast, if the same installation were to only be used for electricity generation, it would reach an efficiency of 54% (Van Tulder & van Gils, 2024). The process begins with the fuel being combusted in gas turbine, generating kinetic energy, which is converted into electricity by a generator. Simultaneously, the heat produced during combustion, which would otherwise be wasted, is captured and used for district heating. This dual production reduces fuel consumption and lowers greenhouse gas emissions, making CCGTs an efficient and relatively environmentally friendly energy solution.

LW06	MK12
247 MW_e	224 MW_e
180 MW_{th}	180 MW_{th}
427 MW_{total}	404 MW_{total}

Table 1.1: The electric (MW_e), thermal (MW_{th}), and total (MW_{total}) capacities of LW06 and MK12

In addition to the CCGTs Eneco operates three gas-fired boilers of 35 MWth each, two biomass installations of 30 MWth each, two E-boilers of 10 MWth each, and one black-start unit of 10 MWe to ensure backup power in case of blackout, all located at production facilities LW and MK. In addition to these thermal energy sources, Eneco operates three auxiliary gas plants located at various heat transfer stations to support peak demand, providing an additional 238 MWth combined (Van Tulder & van Gils, 2024). Furthermore, Eneco is currently testing their new aquathermal heat pump to extract waste heat from the residual flow of wastewater treatment. Expected to generate 27 MW, the largest heat pump of the Netherlands will provide heat to a total of 20.000 homes (Eneco, 2022). Therefore, while fossil fuels remain the primary energy source in Utrecht, Eneco has been making strides in transitioning towards carbon-neutral assets. Currently, they have a total of 80 MW of such assets, accounting for approximately 6.3% of Eneco's overall energy supply in the city and 13.3% of heat supply.

1.2. RESEARCH QUESTIONS AND OBJECTIVES

Recognising the importance of capacity optimisation within renewable energy systems, the objective of this study is to adopt a standard approach to such optimisation problems. The adopted optimisation approach will be applied within the context of Utrechts DHN to answer the following research questions:

What is an effective approach to capacity optimisation in renewable energy systems that integrate thermal and power sources with hybrid energy storage?

To answer this research question, the following sub-questions have been formulated:

1. What decision variables, and objectives, are identified in the literature, and what are the trade-offs between them?
2. Which optimisation algorithms or combination of algorithms are identified in scientific literature and what insights do they provide?
3. What system design considerations and trade-offs are important to the energy system in Utrecht?
4. Which system components are of importance in Utrecht and what are their dependencies?
5. Which level of resilience can be achieved and what is the comparative resilience of a systems designed for multi-year reliability compared to those optimised for typical day scenarios?

2

Literature review

As a result of the intermittency observed in renewable energy sources, the exploration of various energy storage systems (ESS) has become increasingly important in scientific literature (Huang et al., 2024). Energy storage systems mitigate the variability of renewable energy sources, reducing curtailment, and the need for backup systems to meet peaks in demand (Wang et al., 2022). Each storage technology offers distinct advantages and challenges, influenced by factors like round-trip efficiency and energy density (Huang et al., 2024). ESS need to be capital-efficient, practical, energy efficient, durable, and secure. Currently, most energy storage solutions struggle to address multiple requirements at once (M. Liu et al., 2023). Implementing a variety of ESS in a multi-storage system enhances system flexibility, reliability, and economy by effectively balancing out the shortcomings of each individual storage technology (Wang et al., 2022).

Recent research has shown that such hybrid renewable energy systems have the potential to nearly increase capacity factors twofold while improving a range of economic indicators by up to 30% (Hamilton et al., 2020). More specifically, recent research on hybrid integration of battery and thermal energy storage shows improved economy by balancing power and thermal loads simultaneously, thereby reducing grid electricity purchases. Integrating hybrid thermal and power storage improves economic performance by 13.4% and reduces CO2 emissions by 24.6%, due to a 53.9% decrease in renewable energy curtailment (Tooryan et al., 2020; Wang et al., 2022).

Huang et al. (2024) identifies two approaches to optimization in energy systems: single- layer optimization and two-layer optimisation. In the two-layer method, sizing and operational dispatch optimizations are conducted sequentially using heuristic algorithms like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO). While heuristic algorithms provide satisfactory solutions quickly, they don't guarantee the global optimum.

Conversely, the single-layer method integrates sizing and operational dispatch optimization, using Mixed-Integer Linear Programming (MILP) to achieve globally optimal solutions derived from real-time and forecasted data (Huang et al., 2024). This method treats both size and operational parameters as variables optimized concurrently, often resulting in lower energy costs. However, computational challenges may arise with increasing constraints and data, requiring the use of clustering techniques like k-means to manage computational loads effectively by simplifying time series data. This approach strives to balance computational efficiency with solution accuracy in complex, hybrid energy systems (Huang et al., 2024).

Huang et al. (2024) present a model focusing on enhancing energy self-sufficiency and minimizing annual total costs through a mix of technologies including photovoltaic (PV), battery energy storage (BES), thermal energy storage (TES), and hydrogen energy storage (HES). Implementing a Mixed-Integer Linear Programming (MILP) approach, the research strategically optimizes the capacity configuration of these technologies over a one-year period whilst optimising economic dispatch. Notably, Huang et al. incorporates annual hourly data clustered using k-means to simplify the problem space while retaining critical temporal dynamics.

T. Liu et al. (2022) provide a noteworthy contribution through their exploration of system configurations that incorporate an array of technologies including PV, concentrated solar power (CSP), electric heaters, TES, and BES. The study employs a logic-based dispatch strategy coupled with the NSGA-II genetic algorithm to optimize system configuration over a one-year time horizon. The primary objective of their optimization is to enhance the economic performance of the renewable energy system, measured in terms of Levelized Cost of Energy (LCOE) and Loss of Power Supply Probability (LPSP), which are critical indicators of both cost efficiency and reliability. The decision variables in this study include the capacity of the various technologies, expressed in MW for generation capacities and MWh for storage capacities.

Tooryan et al. (2020) presents an optimisation model focusing on the integration of multiple energy technologies, including wind power, PV, electric boilers, BES, TES, and HES. The primary objective of this study is to minimize costs, greenhouse gas emissions, and fuel consumption over a one-year period, employing a rule-based dispatch strategy. This approach highlights the interplay and trade-offs between economic and environmental performance in hybrid energy systems. To achieve these objectives, the authors apply PSO, a technique well-suited for tackling the complex, multi-dimensional decision variables such as the capacities of system components.

M. Liu et al. (2023) provides an analysis that integrates multiple energy technologies including wind, PV, thermal energy, Compressed Air Energy Storage (CAES), BES, TES, and HES. The study is driven by objectives to minimize both the costs associated with energy production and the capacity of the storage systems utilized. To meet these goals, Liu employs a genetic algorithm, a powerful tool for finding efficient solutions across complex and diverse system configurations. The optimization is applied to yearly data, although it is not specified whether the method consolidates this into a representative 'typical day' approach, which is a common technique in long-term system studies to reduce computational demands while capturing critical variability. The decision variables in this study focus on the capacities of the various technologies, which underscores the strategic intent to optimize system sizing. The use of rule-based dispatch in conjunction with genetic algorithms allows the study to address real-world operational challenges, ensuring that the solutions are not only cost-effective but also viable under typical operational conditions.

In the exploration of optimizing a diverse energy portfolio, Potrč et al. (2023) focuses on an extensive array of energy sources including biofuel, PV, wind, geothermal, hydro, nuclear, and fossil fuels, alongside various energy storage technologies such as CAES, Phase Change Materials (PCM), Pumped Hydro Storage (PHS), BES, Thermal Chemical Storage (TCS), and TES. The objective of this comprehensive study is to maximize sustainability, defined through a holistic lens that incorporates economic, environmental, and social factors. The approach employs MILP for both system dispatch and optimization. The study spans a forward-looking time horizon towards 2050, segmented into 10-year intervals, with data granularity extending down to monthly, daily, and hourly intervals. This long-term analysis is crucial for understanding the dynamics of energy production and consumption transitions in response to evolving technological, economic, and policy landscapes. Decision variables in the model are quantified in terms of the output from each technology, measured in terawatt-hours (TWh), providing a clear metric for assessing the contribution of each energy source to the overall system sustainability.

Research by Wang et al. (2022) addresses the complex challenge of optimizing energy systems that integrate diverse sources such as wind, photovoltaic, and fossil fuel power plants, alongside BES and TES systems and heat pumps. The primary objective of Wang's study is cost minimization, which is tackled through a robust two-step optimization process. Initially, the enumeration method combined with a genetic algorithm is used to plan the number and location of energy resources. Subsequently, Mixed Integer Non-Linear Programming (MINLP) is employed for the capacity optimization of these resources. This approach allows for a nuanced exploration of spatial and quantitative aspects of system design, ensuring that both the geographic distribution and the scale of energy solutions are optimized for cost-effectiveness. The study utilizes a typical-day scenario for modelling, thereby reducing computational requirements.

In a study conducted by Zheng et al. (2018), a comprehensive optimization approach is utilized to enhance the integration of various renewable and storage technologies including a biomass gasifier, PV, wind, TES, BES. The main objective of this research is to minimize cost through a detailed analysis performed over a 27-hour time horizon. Zheng employs a two-layer optimisation approach, optimising system sizing before operation. The sizing optimisation focuses specifically on determining the optimal capacities for wind and solar energy production, highlighting these as critical decision variables. These capacities are optimised through a brute force method, which, despite its computational intensity, ensures a thorough exploration of all possible combinations of system configurations. This approach, coupled with a linear constrained optimization dispatch strategy, systematically evaluates how different configurations impact overall system performance and cost-efficiency.

In his analysis, Hamilton et al. (2020) explores an approach to optimizing dispatch in energy systems that integrate PV, CSP, TES and BES. The primary objective is to maximize profit, which is particularly challenging given the variability in energy production and market prices. Hamilton employs MILP to optimize dispatch strategies, focusing specifically on achieving the most profitable operation. The optimization covers a time-horizon of two days, distinguished by varying time steps: the first day utilizes 10-minute intervals, allowing for fine-grained adjustments in response to rapid changes in solar intensity and demand, while the second day uses one-hour timesteps, aligning more closely with typical energy market trading intervals. This temporal differentiation in the model is key to its computational efficiency, reducing solve time by 79%.

Research by Jacob et al. (2023) employs an approach to optimizing renewable energy system that incorporates wind, biomass, PV, HES, TES, BES. The study aims to minimize annual operational costs, using MILP to model and optimize the system's performance. The optimization is applied to hourly data over a full year, strategically clustered into 12 monthly periods each containing 136 hourly clusters to manage computational complexity while capturing seasonal and hourly variability. The primary decision variable in this optimization is the capacity allocation among the various technologies, which is crucial for achieving an optimal balance between investment costs and operational efficiency.

The findings from the reviewed literature align with a recent meta-analysis of 241 scientific studies focusing on the optimization of ESS sizing. According to Tahir (2024), the majority of these studies (94%) utilized data spanning one year, with 81% containing hourly resolution. In terms of optimization scope, 94% of the studies focused on single-day scenarios. Regarding the technologies studied, 65% of the papers focused on optimizing the sizing of BES, while 29% examined hybrid systems combining different storage technologies. Notably, 46% of these studies applied meta-heuristic optimization methods, with Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO) being the most popular (Tahir, 2024). Additionally, 13% of the studies employed Mixed-Integer Linear Programming (MILP) as their optimization technique.

2.1. KNOWLEDGE GAPS

Hybrid energy systems have become an important area of research over the past years as they provide a promising solution to the challenges of the energy transition. However, despite significant advancements in recent years, there remain several knowledge gaps that warrant attention. Within the reviewed literature, these knowledge gaps can be categorized into three main areas.

Firstly, several studies overlook the potential application of TES for providing heat. Instead, they concentrate on using TES primarily for power storage, often referred to as Carnot batteries. However, by disregarding stand-alone TES solutions, these studies overlook the fact that heat demand can be satisfied more affordably using stand-alone TES systems. Therefore, hybrid renewable energy systems, particularly those that integrate district heating networks for the provision of heat, are often overlooked in these studies, despite their potential to offer more cost-effective and sustainable solutions for meeting heat demand.

Secondly, several studies have performed incomplete optimisation by focusing solely on emissions or capital expenditures, neglecting to consider the operational expenditures. Additionally, some studies have failed to optimise system component sizing, instead focusing on energy management within existing fossil- fuel-based infrastructure. Thereby adopting a backwards looking approach rather than a forward looking one.

Thirdly, several studies have modelled an incomplete representation on the future energy infrastructure by focusing on solely renewable electricity in the form of PV and wind power. Thereby, failing to recognise that heat demand can also be satisfied through sustainable heat sources such as geothermal, biomass, and industrial waste-heat.

In addition to these three main knowledge gaps, there is very limited research performing optimisation across larger datasets. Instead, most optimisation studies use either average monthly or daily data, failing to design systems with reliable power supply on smaller timeframes (Hamilton et al., 2020; Huang et al., 2024). To accurately optimise system components for economy and reliability, it is important to model hourly or even sub-hourly data that considers the time-of-production value of energy. However, optimisation of models with such high-fidelity energy generation, demand, and storage data have been shown to be computationally expensive to solve (Hamilton et al., 2020). To improve solution times, Hamilton et al. (2020) offer techniques that decreases solution time by up to 93% for an annual model. While there are limited studies that do include higher fidelity data, these are limited to a single year, potentially overlooking variations in generation and demand patterns across multiple years. Finally, none of the studies have been performed within the Dutch energy infrastructure. Therefore, due to varying climate conditions, previous findings might not be directly generalised to the Dutch grid.

Following this analysis, we conclude that none of the reviewed studies evaluate hybrid energy systems that incorporate district heating networks with a forward-looking asset analysis, high-fidelity data to accurately represent the time value of energy, and a holistic objective approach. Due to these knowledge gaps, implications on hybrid system size and scalability, particularly regarding costly energy storage, and the total performance of the system remain insufficiently understood, warranting the adoption of a comprehensive optimal system sizing approach from a systems engineering perspective.

3

Thermal energy storage

Thermal Energy Storage is crucial for the energy transition in the Netherlands given its high thermal demand. The integration of TES systems can adress both short-term and long-term storage needs, making it a key component in managing energy requirements efficiently. This chapter will examine the different categories of TES technologies and further explore the ones that are technically feasible within Utrecht's DHN. By exploring different implementations of TES, we will demonstrate how these systems can provide reliable energy solutions that are capable of handling both immediate fluctuations and seasonal demands.

3.1. Latent Thermal Energy Storage

Latent thermal storage uses phase change materials (PCMs) that store or release heat at a constant temperature during a phase change process (IRENA, 2020). This type of TES is particularly beneficial for applications requiring consistent temperature control, as the PCM maintains a constant temperature during the phase transition, providing a stable thermal reservoir. One of the key advantages of latent heat storage is its high energy density, as PCMs can store large amounts of thermal energy within a relatively small volume. A common example of latent heat storage is the application of ice-based thermal energy storage systems in commercial air conditioning systems. During off-peak hours when electricity demand is low, ice is produced using surplus energy and subsequently stored. During high cooling demand periods, the stored ice is melted to provide cooling. Despite its advantages, latent heat storage systems may be limited by the availability of suitable PCMs and the need for careful thermal management to prevent phase separation or degradation of the storage material over time. Furthermore, the most suitable PCMs are burdened by low thermal conductivity, which limits the charge and discharge rate (IRENA, 2020).

While research on latent thermal storage has been increasing in recent years, its cost is not competitive with sensible storage. Additionally, there are no commercially available large-scale latent storage technologies available. Therefore, while PCMs could be a valuable technology for future DHNs, we will not consider them in this study.

3.2. THERMOCHEMICAL THERMAL ENERGY STORAGE

Thermochemical storage involves the use of chemical reactions to store thermal energy. According to IRENA (2020) this type of TES offers high energy density and the potential for long-term, loss free storage, making it particularly suitable for applications that require large-scale energy storage over extended periods, such as seasonal storage (Figure 3.1). Thermochemical storage systems typically utilize reversible chemical reactions that absorb heat when the reaction proceeds in one direction and release heat when the reaction is reversed. One example of thermochemical storage is the use of metal oxides, such as calcium oxide (lime), which can undergo exothermic reactions with water to produce heat. During periods of excess energy supply, the metal oxide is heated and chemically transformed into its dehydrated form, storing thermal energy in the form of a solid. Later, when heat is needed, the dehydrated oxide is exposed to water vapour, triggering an exothermic reaction that releases heat.

Although thermochemical storage offers significant advantages in terms of energy density and long-term storage capability, it is often complex and expensive to implement, requiring careful control of reaction conditions and the use of specialized materials. Furthermore, the required materials are often highly reactive in nature, resulting in corrosion and material degradation (IRENA, 2020). Due to these complexities, there are currently no large-scale thermochemical thermal energy storage systems available that could be implemented in DHNs. Therefore, while thermochemical systems could be valuable for future DHNs, we will not consider them in this study.

3.3. SENSIBLE THERMAL ENERGY STORAGE

Sensible thermal energy storage relies on the heat capacity of various materials. In these systems, energy is stored by raising the temperature of a material, such as water or rocks, during times of surplus energy supply (IRENA, 2020). This type of TES is widely used due to its simplicity, reliability, and cost-effectiveness. The stored heat can later be extracted to meet heating demands. One clear example of sensible heat storage is the use of hot water tanks in residential and commercial buildings. These tanks store hot water generated by solar panels or other RES during the day and release it for space heating or domestic hot water use during periods of high demand. While sensible heat storage systems are relatively straightforward to implement and operate, they are limited by the relatively low energy density of their storage materials, which may require large storage volumes to meet high energy demands. The amount of energy stored (kWh) in a sensible TES system is described in equation 3.1.

$$Q = \frac{mc\Delta T}{3,6 * 10^6} \tag{3.1}$$

Where, Q represents the thermal storage in kWh, m the mass of the medium, c the specific heat capacity of the medium, and ΔT the temperature change in kelvin. The constant 3.6×10^6 converts the units to the desired form.

Sensible TES systems lose their thermal energy over time due to convection and conduction. Conduction is the transfer of heat within or between materials solid materials.

Convection, on the other hand, is the transfer of heat by the movement of fluids. The rate of energy loss from a sensible TES system in watts is described in equation 3.2.

$$q_t = (UA)\Delta T_t \tag{3.2}$$

Where U represents the overall heat transfer coefficient, A the surface area in m^2, and ΔT_t the temperature difference in Kelvin at time t.

From these equations, we can discover three important trade-offs. First, a larger temperature difference allows for greater energy storage capacity, but also comes with higher energy losses. Second, there exists a crucial relationship between the mass and surface area of a system. As the mass increases, so does the surface area of a system. While a high mass is necessary for a high energy storage capacity, a high surface area leads to greater energy losses. Initially, this might seem like a trade-off between capacity and energy loss; yet the issue is more nuanced. Increasing an object's mass increases its surface area, but the ratio of surface area to mass tends to decrease. Therefore, a larger storage volume will lose less energy as a percentage of the total storage capacity, even though its absolute energy loss is higher. Finally, the loss of a sensible TES system is a function of time. Therefore, a system will lose more thermal energy if the intended storage duration is extended. In any thermal storage system, these trade-offs can be mitigated by increasing the insulation (U) albeit at the expense of increased system costs. According to IRENA (2020), there are four primary sensible TES technologies available: water tank, underground, Solid-state, and molten salt thermal energy storage (Figure 3.1).

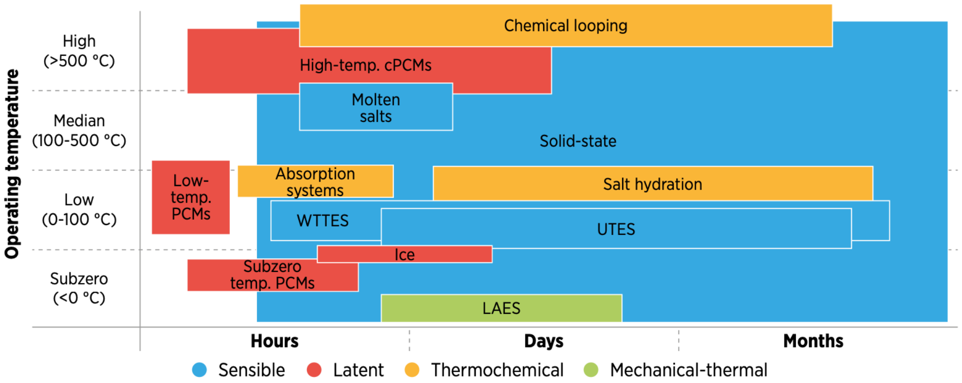

Figure 3.1: An overview of different TES technologies sorted by operating temperature and storage duration (IRENA, 2020)

3.3.1. TANK THERMAL ENERGY STORAGE

Tank Thermal Energy Storage (TTES) is a crucial technology in the TES field, offering high efficiency for integrating renewable energy sources by utilizing water's high specific heat capacity to store and release thermal energy within insulated tanks. This process utilizes the sensible heat of water, storing energy as the water heats and releasing it as the water cools. These systems, similar to residential hot water cylinders, consist of steel or reinforced concrete tanks with insulation to minimize thermal losses. Heat exchangers and pumps facilitate the efficient transfer and circulation of heat, regulated by a control system to match demand.

A crucial aspect of TTES efficiency is thermal stratification, which maintains distinct temperature layers within the tank, allowing the hotter water at the top to be used on demand without additional heating. This stratification enhances responsiveness, conserves energy, reduces operational costs, and minimizes thermal losses by keeping cooler water at the bottom, acting as a natural insulator for the water above. This efficient layering ensures rapid and effective energy delivery and maintains overall system efficiency (IRENA, 2020).

TTES systems utilize the high specific heat capacity of water to efficiently store and release thermal energy, making them ideal for applications across residential and municipal scales. These systems are characterized by their simplicity, which contributes to their reliability, low maintenance, and cost-effectiveness. Additionally, the ability of TTES to minimize energy losses through advanced insulation techniques and maintain thermal stratification enhances their efficiency, making them a practical choice for integrating into district heating systems and aligning with sustainable energy goals. However, challenges such as limited storage capacity at standard pressure and the resulting need for more complex, pressurized systems to achieve higher temperatures pose limitations that require careful consideration.

3.3.2. SOLID-STATE THERMAL ENERGY STORAGE

Solid State Thermal Energy Storage (SSTES) offers a valuable solution for energy storage in environments where space is limited or high temperatures are required. SSTES utilises the heat capacity of solid materials such as rocks, ceramics, and composites, commonly incorporating cost-effective and readily available materials like sand, concrete, and brick due to their favourable thermodynamic properties (IRENA, 2020).

These systems function by absorbing and releasing heat through sensible heat storage, where solid materials store energy as they warm up during periods of excess energy generation and release it when demand rises. Encased in well-insulated tanks, SSTES stores energy within these solids, and when needed, transfers it via a working fluid through a heat exchanger to the DHN, enhancing energy utilization and system efficiency.

SSTES systems are particularly effective for industrial processes where high temperatures are required. Additionally, SSTES systems are suitable for applications where spatial requirements pose significant constraints such as densely populated urban areas. The high operating temperature allows SSTES to achieve a superior energy density over traditional TTES, despite solids typically having a lower specific heat than water. The simple structure of SSTES, including insulated tanks and simple heat exchange systems, lends itself to reliability, reduced maintenance costs, and improved safety due to the noncorrosive nature of materials like sand and their reduced risk of leakage. However, SSTES's high operating temperatures also lead to higher energy losses, though the low thermal conductivity of materials like sand helps limit these losses over time by forming an insulating layer around the hotter core. Additionally, SSTES can produce both direct heat and, at high temperatures, generate electricity, similar to combined heat and power (CHP) systems, enhancing its overall application and exergy.

3.3.3. UNDERGROUND THERMAL ENERGY STORAGE

Underground thermal energy storage (UTES) refers to the storage of thermal energy in various underground applications. Although UTES can be used for short-term storage, it is usually intended for seasonal storage. There are four common types of UTES: tank, borehole, aquifer, and pit. Each of these technologies has its own advantages and disadvantages. For seasonal applications, aquifer thermal energy storage (ATES) is not only the most efficient technology, but also the cheapest (Pauschinger et al., 2018). Additionally, ATES has the lowest spatial requirements which could be an essential decision criterion in densely populated urban areas. Furthermore, Eneco has already conducted research on the feasibility of ATES implementation in Utrecht, revealing that the geological conditions are exceptionally well-suited for ATES in the region (Remmelts, 2019). Due to its favourable characteristics and existing research, this chapter will focus on ATES as the primary underground storage technology (Figure 3.1).

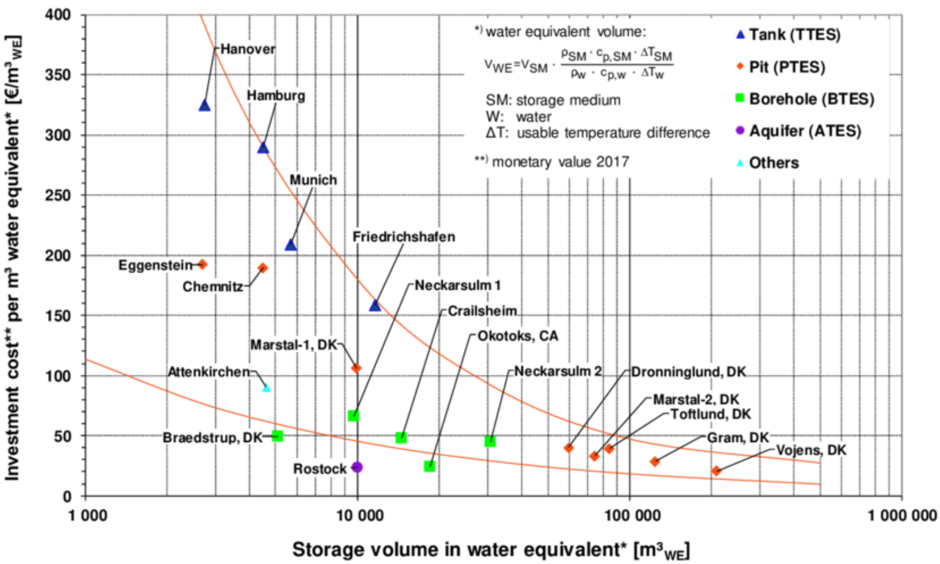

Figure 3.2: Price curve for the four most common underground thermal energy storage technologies showing the relationship between system size and costs (Pauschinger et al., 2018)

ATES is a sustainable technology that efficiently manages thermal energy by taking advantage of natural underground water formations, known as aquifers, to store and retrieve heat based on seasonal demands. This system is particularly advantageous in areas with significant temperature variations between seasons. ATES systems can be implemented in two configurations: high-temperature ATES (HT-ATES) and low-temperature ATES (LT-ATES). Both variations operate by creating two wells within subsurface groundwater layers contained by permeable rock, also called aquifers. One well stores thermal energy in the form of warm water, whereas the other stores cool water. During surplus energy periods, excess heat is stored in the warm well and later extracted during higher demand periods through a heat exchanger mechanism, improving energy usage efficiency and reducing dependence on conventional sources (IRENA, 2020). As ATES discharges, the temperature of the warm well decreases. To continue operations at a consistent output temperature, ATES is often paired with a heat pump.

ATES is praised for its cost-effectiveness and minimal spatial impact, which makes it suitable for seasonal energy storage in densely populated urban areas. Despite its advantages, the implementation and ongoing efficiency of ATES systems are heavily dependent on local geological conditions. Moreover, system maintenance is crucial as inefficiencies such as well clogging and material degradation can impact performance over time (Pauschinger et al., 2018). Environmental concerns also exist, particularly the potential alteration of local groundwater temperatures, which could affect ecosystems. However, a study covering the period from 2016 to 2018 demonstrated minimal net impact on groundwater temperatures, suggesting a balanced thermal input and output in ATES systems (Fleuchaus et al., 2020). This finding underscores the potential of ATES for sustainable energy management with proper regulatory compliance and ecological monitoring.

3.3.4. MOLTEN SALT THERMAL ENERGY STORAGE

According to IRENA (2020), molten salt thermal energy storage (MSTES) is a valuable technology primarily used in high-temperature applications, especially within concentrated solar power plants. In these systems, MSTES captures thermal energy during peak sunlight hours and releases it during off-peak hours to ensure consistent power generation. MSTES operates by heating salts, to high temperatures. A standard MSTES configuration uses a two-tank system: one tank stores “cold” molten salt, and the other stores “hot” molten salt. When power generation is required, the hot molten salt is directed through a heat exchanger to produce steam, which drives a turbine. Afterward, the cooled salt returns to the cold tank. Despite its advantages, MSTES has several challenges. A primary issue is the risk of salt solidification, which can damage system components and impact reliability (IRENA, 2020). Additionally, molten salts are corrosive and require careful handling in highly controlled environments. The system is also constrained by the salts’ high freezing point, necessitating significant energy input to keep the “cold” tank above freezing, which increases operational costs. Given these complexities, MSTES is typically limited to short-term thermal storage applications for power production, where its high temperature stability can offset these operational demands (IRENA, 2020).

4

METHODOLOGY

This chapter outlines the methodological framework employed to address the optimisation of hybrid renewable energy systems, focussing on multi-objective considerations that integrate both thermal and power sources along with hybrid energy storage systems. The complexities inherent in designing such systems requires a robust analytical approach that can navigate multiple objectives and conflicting constraints, which are typical in the optimization of energy systems. The proposed approach is designed to achieve a comprehensive understanding of the trade-offs and interactions between various system components and objectives. This involves a detailed system characterisation, the selection and implementation of suitable optimisation algorithms, and rigorous system simulations. The overarching aim is to derive actionable insights that can guide the real-world design of energy systems.

From the literature review it has become clear that there is no standardised approach to multi-objective optimisation in hybrid renewable energy systems. Therefore, it is important to develop and adopt a standardised optimisation approach. In this chapter we will describe and adopt such an approach for optimisation using learnings from the scientific literature. From the literature, it has become clear that there are three key steps to optimisation of energy systems: system design, model development, and optimisation design.

The framework starts with the definition of the system design, encompassing the scope, system boundaries, and the included system components and their dependencies. Following this, the model development is elaborated in detail. This section encompasses various input data pertaining to individual system components, as well as demand and supply profiles. These inputs serve as the foundation for the creation of a mathematical model that accurately represents the dynamics and interactions within the hybrid renewable energy system. Subsequent to model development, the optimisation design is discussed, including the objectives of optimisation and the identification of key decision variables and constraints that influence system performance. Thereafter, the selection process for the optimisation algorithms most suitable to our multi-objective framework is detailed, with a discussion of their merits and limitations within the context of our specific application.

Following the optimization design, the analysis of results will be described, focusing on the diverse outcomes across various scenarios. The optimised system configurations will be subjected to testing under alternative situations with different supply and demand profiles to evaluate the robustness of the configurations. This phase aims to ensure that the proposed solutions maintain their efficacy and reliability under varying conditions, thereby confirming their practical applicability and resilience in real-world settings.

4.1. FRAMEWORK

Modern energy systems are increasingly complex due to the integration of renewable energy sources, deregulated energy markets, evolving technology, and multi-actor dynamics. This complexity necessitates sophisticated optimization techniques to manage energy generation, distribution, and consumption efficiently. Optimization strategies can accommodate the unpredictability of renewable sources, such as wind and solar, thereby supporting sustainable energy transitions. To ensure such optimisation can be performed reliably and effectively, this chapter will describe a framework to capacity optimisation in energy systems. The framework consists of five crucial steps: multi-actor analysis, system design, optimisation design, model development, and analysis of results (Figure 4.1).

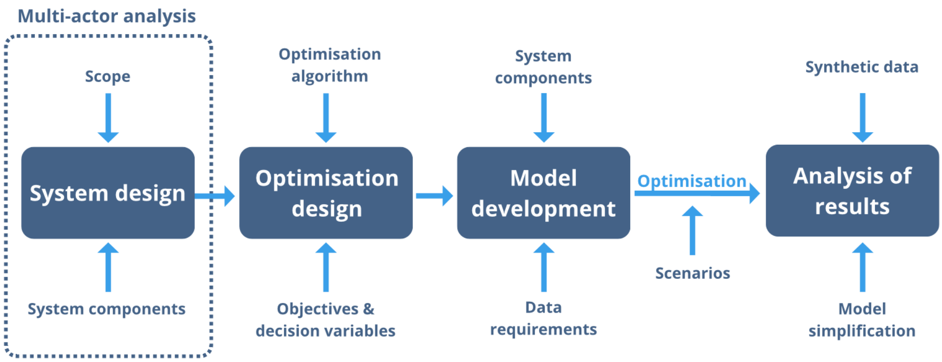

Figure 4.1: Optimisation framework in four steps

The first step, multi-actor analysis, is essential to understanding the context and political complexities in which the system will be designed. By identifying and analyzing key stakeholders, potential collaborations and threats can be uncovered.

Following this, system design is crucial for optimizing energy systems. The design must consider not only technical aspects but also the political landscape revealed during actor analysis to ensure a well-rounded solution that aligns with stakeholder interests and broader energy transition goals. A well-defined system design determines what components like generation, transmission, distribution, and consumption are included and how they interact with each other. A comprehensive understanding enables effective identification of bottlenecks and opportunities for improvement within the system. Additionally, a clear system design aids in predicting system behavior under various conditions, facilitating better decision-making. It also ensures that the system can adapt to changes in demand, regulatory requirements, and technological advancements. This step requires careful consideration as an otherwise flawless optimisation, including the wrong components, does not lead to the right strategic insights. Furthermore, optimization design involves a number of careful considerations. It is crucial to clearly define the objective, decision variables, algorithm, period, and potential scenarios. This requires a detailed assessment of the factors that can be influenced by the problem owner, in this case, Eneco. Following the optimization design, the system design can be translated into an operational optimization model. This model requires detailed modeling of system components, their interdependencies, and relevant data. Finally, after running the model across different scenarios, the results must be analyzed. This analysis includes testing the performance but also the robustness of the optimized setup under various circumstances.

4.2. MULTI-ACTOR ANALYSIS

In the energy transition, a key challenge lies not only in the technical aspects but also in the complexity of relationships between the various stakeholders involved. A multi-actor analysis is essential to understanding how these stakeholders interact, influence decision-making processes, and shape the outcomes of energy projects. By analysing the actors and their relationships, we can identify potential conflicts, align incentives, and foster collaboration, which is crucial for the successful implementation of energy solutions.

4.2.1. STAKEHOLDER IDENTIFICATION

There are multiple important stakeholders included in EPU's transition. In this chapter we will discuss six of the most important stakeholders and their power and interest in the transition to renewable thermal energy.

Energy production Utrecht

EPU is an important actor as it both owns and operates the DHN in Utrecht. EPU is considered the problem owner, being the primary actor responsible for transitioning Utrecht's DHN, with the necessary means to do so. EPU's primary objective is to be climate neutral by 2035 by providing renewable energy for everyone (Eneco, 2024f). However, as Eneco is a commercial entity, another key objective is to maximize profitability, which often directly competes with the goal of climate neutrality. From the means-end analysis, we can identify three primary actions to reach sustainability goals while continuing profitable business operations: investment in renewable energy infrastructure, investment in power-to-heat, and investment in energy storage (Appendix B.2).

Investment in energy storage

Investment in energy storage is the most versatile action EPU can take to achieve its goals. This investment would reduce peak demand, enabling more homes to connect to the DHN and driving business growth. It also supports the expansion of renewable energy capacity by mitigating the intermittency of RES while generating significant profitability. Finally, as supply and demand become more balanced, energy prices would stabilize, making energy more affordable for consumers.

Investment in renewable infrastructure
Investment in renewable infrastructure, particularly in district heating networks (DHNs), would allow EPU to supply more homes, driving business growth. Additionally, it would increase the share of renewable energy capacity, as DHNs emit fewer emissions than traditional residential heating systems. Furthermore, DHNs enable large-scale seasonal thermal energy storage, which further increases the renewable energy share during periods of low output from RES.

Investment in power-to-heat
Finally, investing in P2H would enhance EPU's sustainability by increasing the renewable share in thermal production. Additionally, it boosts profitability, as P2H is highly efficient and allows for strategic heat production based on power prices, similar to demand-side response. The combination of high efficiency and demand-side response helps lower energy costs for consumers while contributing to a more sustainable energy system.

National government (EZK)
The national government and in particular the ministry of economic affairs and climate (EZK) has set ambitious goals for the energy transition. The main objective of the ministry of EZK is to create and maintain a sustainable and entrepreneurial economy (Economische zaken en klimaat, 2024). The main objective is supported by multiple sub-goals (Appendix B.3). One important sub-goal is the development of sustainable infrastructure. Within this goal, district heating networks have become a crucial focal point of the Dutch energy transition and an integral part of the sustainability agenda. Recognizing their potential, the government aims to double the number of households connected to DHNs, targeting an additional 500,000 households by 2030 (Rijksoverheid, 2023). Like the local government, the national government's policy for renewable thermal supply is based on three primary objectives: the supply must be renewable, affordable, and reliable. To achieve its goals, the government has several policy instruments at its disposal, which are often more powerful than those available to local governments. From the means-end analysis, we can identify three primary policy instruments: financial incentives, regulation, and public-private partnerships (Appendix B.3).

Financial incentives
The financial incentives is the most widely applicable policy instrument that the government has at its disposal. Financial incentives include subsidies, tax incentives, and low-interest loans to stimulate investment and innovation in sustainable energy infrastructure, as well as carbon pricing to discourage investment in fossil fuel-based alternatives.

Regulation
Another powerful policy instrument is regulation. Measures such as prohibiting the replacement of old gas infrastructure and banning new gas infrastructure in newly built properties can force investment in renewable energy infrastructure. The government can further enforce this by mandating a minimum percentage of renewable energy production for energy companies. Additionally, renewable energy use can be promoted by ensuring fair pricing for consumers, as seen with the Authority for Consumers and Markets (ACM), which sets price ceilings for district heating networks (DHNs).

Public-private partnerships
Finally, the government can introduce public-private partnerships in the form of joint ventures to stimulate innovation in the energy sector by supporting energy startups. Furthermore, such joint ventures could facilitate investment in areas where markets would otherwise fail.

Municipality of Utrecht
The municipality of Utrecht has set an ambitious goal of becoming climate neutral by 2030. To achieve this, 10,000 properties must be decoupled from natural gas each year (Gemeente Utrecht, 2017). The city's main objective is to create a livable city for everyone (Gemeente Utrecht, 2024c). Heat provision is a top priority, as one-third of the city's emissions stem from thermal demand. In response, the municipality developed a "thermal vision," which outlines its strategy to transition to renewable thermal sources. This vision is centered around three key objectives: the heat supply must be renewable, affordable, and reliable (Gemeente Utrecht, 2017). To meet these goals, the municipality has several policy instruments at its disposal: permits, subsidies, and public-private partnerships (Appendix B.4).

Subsidies
The most versatile policy instrument at the municipality's disposal is subsidies. In the context of the energy transition, the municipality can offer subsidies to support the expansion of the DHN and renewable energy capacity to meet its sustainability goals. Additionally, the municipality can offer subsidies to citizens to encourage investment in renewable energy solutions, such as PV and heat pump systems, or to help lower energy costs.

Permits
Another powerful policy instrument is the issuance of permits. Through permits, the municipality can prioritize developments that align with its sustainability goals. A recent example is the municipality's sale of land and the issuance of a permit to Eneco for the construction of a tank thermal energy storage unit in Nieuwegein. Conversely, the municipality can also withhold permits to block developments that do not align with its objectives.

Public-private partnerships
Similarly to the national government, municipalities can form public-private partner-

ships. This way, the municipality can stimulate sustainability projects in markets where they would otherwise fail.

Grid operators

Grid operators (GOs) play a crucial role in the energy transition. As supply and demand has become increasingly unbalanced due to intermittent renewable energy sources, grid operators have faced rising grid congestion and challenges with frequency regulation. Their main objective is to provide reliable grid connections, thereby facilitating the energy transition (TenneT, 2024a). They do so by ensuring the continuation of profitable business operations and improving grid stability. From the means-end analysis, we can identify three possible actions for GOs to reach their goals: investment in grid connections, demand-side response, and curtailment (Appendix B.5).

Demand-side response

Demand-side response (DSR) is a versatile solution for reducing grid congestion by balancing supply and demand, while also increasing profitability by avoiding costly maintenance and repairs caused by peak surges. Furthermore, it supports growth by enabling more grid connections through reduced peak demand. GOs can implement DSR directly via battery energy storage systems, which charge during high RES availability and discharge during peak demand load. Additionally, GOs can require DSR for new connections or incentivise businesses with tariff discounts.

Curtailment

Curtailment is another possibility to improve grid stability and ensure growth. By requiring RES connections to curtail their energy production during peak supply hours, grid strain can be eased. Additionally, curtailment can be incentivised with tariff discounts.

Grid investment

Another possibility is to invest in the grid by improving the capacity of its connections. TenneT, the high-voltage transmission grid operator in the Netherlands, plans to invest €111 billion in the grid in the coming years, aiming to double or even quadruple grid capacity by adding 2,500 km of new transmission lines (Tennet, 2024). Such investment would increase the peak capacity and consequently allow for new connections and growth.

Local community

Another important stakeholder is the local community in Utrecht. Not only are they EPU's customers, purchasing thermal energy through the district heating network, but they can also present challenges during project development. Their primary goal is to create and maintain an enjoyable living environment. Two key sub-goals to achieve this include fostering a sustainable environment with access to renewable energy at affordable prices and developing vibrant outdoor spaces such as parks and recreational facilities. From the means-end analysis, we can identify four possible actions for the local community to reach its goals: local initiative, investment in PV, objection, and contract termination (Appendix B.6).

Local initiative

The most versatile option for the local community is to establish local initiatives. Doing so, they can increase the availability of clean energy through self funded sustainability projects. However, they can also take initiative for the creation and maintenance of green spaces and recreational areas.

Investment in PV

In addition to establishing local initiatives, members of the local community can also invest in private PV installations. This action would increase their renewable energy share and decrease their energy prices.

Objection

Another powerful tool the local community has to achieve its goals is the ability to object to certain developments. Objections can delay or even prevent the issuance of building permits, giving the community a strong negotiating position and, in effect, making them gatekeepers for developments in their neighborhoods. A recent example is the construction of the thermal storage in Nieuwegein, which incurred an additional €200,000 in costs for covering the structure with artwork to help it blend into the surrounding environment (Janse de Jonge et al., 2022).

Contract termination

A very powerful, though not highly versatile, action available to the local community is the option to terminate their thermal contract with Eneco to reduce energy costs. With the widespread availability of efficient residential P2H technologies, such as e-boilers and heat pumps, some community members may find investing in these technologies more cost-effective than remaining a DHN customer. While there are contractual fees for terminating a DHN connection, the 2015 Van den Brul case, where termination fees were waived, sets a precedent that could make future contract terminations free of charge (Geschillencommissie energie, 2014; Rechtbank Midden-Nederland, 2015).

Energy companies

Although Eneco is an energy company, it is still dependent on other energy providers. To operate its CCGTs and peak boilers, EPU relies on a stable gas supply and the corresponding infrastructure. Additionally, as P2H assets take on a larger role in the district heating network, EPU may increasingly rely on other renewable power providers through power purchase agreements, or potentially become more dependent on hydrogen providers and infrastructure in the future. The primary objective of these energy companies is to continue their business operations and maximize profitability. As power is a commodity, the only means to reach this goal it through price mechanism.

4.2.2. POWER & INTEREST ANALYSIS

From this analysis, we can categorize all stakeholders into four groups based on their power and interest in the decision-making process.

- High power, high interest stakeholders are referred to as players. It is crucial to establish close collaboration and strong business relationships with them to ensure their support and involvement.

- High power, low interest stakeholders are known as context setters. The problem owner should regularly consult these stakeholders to ensure their plans and ideas are considered, preventing potential sunk investments.

- Low power, high interest stakeholders are labeled as subjects. While it is important to involve them in the decision-making process, their input is not decisive.

- Finally, low power, low interest stakeholders are referred to as the crowd. The crowd is not actively involved in the decision-making process but should be kept informed about developments.

As the final decision-maker on how its DHN transitions to renewable heat, EPU is a very powerful actor with a high level of interest in the subject. However, it is important to note that its solution space is constrained by the influence of other powerful actors. The ministry of EZK has a strong interest in the national thermal transition as a whole, but less so in the specific transition in Utrecht. Nevertheless, this actor is very powerful as national policies inevitably shape the political landscape in Utrecht and have the potential to significantly impact local decision-making. The municpality of Utrecht has a strong interest in the transition of the DHN and holds significant power to influence the decision-making process. Grid operators wield significant power, as they determine the maximum grid capacity available to EPU. They also have a high level of interest in DHSNs, as these systems can both alleviate and exacerbate grid congestion. However, as their operations span more than just Utrecht, their interest is not as high as that of other high-interest actors. While the local community has relatively high power when it comes to developments in their area, they hold less influence over decisions made at LW and MK. They can however, choose to terminate their contract putting them in a position of power. However, since decisions regarding the DHN ultimately have financial implications for the community, their interest in the transition is high. Energy companies' interest in EPU's transition is medium as they also have other clients that can drive profitability. Eneco's ability to build its own renewable energy assets, along with the option to choose from various energy companies, strengthens its negotiation position. Therefore, this group of actors is not particularly powerful.

Based on this categorization, the key stakeholders include four primary players—EPU, grid operators, the Municipality of Utrecht, and the local community—one key subject, energy companies, and one context setter, the national government (Appendix B.1). The disproportionate number of players in the decision-making process adds complexity to the thermal energy transition. This complexity requires careful consideration and clear communication to ensure successful outcomes.

4.2.3. THREATS AND COOPERATION

Among the five high-power actors, there are multiple conflicting and complementary goals, which present both risks and opportunities for strategic cooperation. To ensure successful outcomes, it is essential that Eneco actively manages these risks while fostering close collaboration wherever possible.

National government
The incentives of the national government and EPU are largely aligned. The Ministry of Economic Affairs and Climate aims to create a sustainable and entrepreneurial economy, while EPU seeks to increase renewable energy usage alongside profitable business operations. This alignment creates opportunities for close collaboration, where Eneco provides renewable energy and contributes to economic growth, while the government may offer financial incentives. However, a small area of friction arises regarding affordable energy prices, as the government's regulation, such as thermal energy price caps and profitability limits, may conflict with Eneco's profitability goals (ACM, 2024). The new "Wet Collectieve Warmte" (WcW) bill could further complicate matters by shifting control to municipalities, potentially lowering DHN tariffs and reducing EPU's decision-making influence. While still under review, the WcW could empower municipalities with stronger regulatory authority over local heat systems and limit Eneco's profitability through cost-based pricing models, creating friction in an otherwise aligned relationship (NPLW, 2024).

Municipality of Utrecht
Similarly to its relationship with the national government, EPU's relationship with the Municipality of Utrecht is largely mutually beneficial. The municipality aims to reduce emissions and increase the use of renewable energy sources, goals that EPU supports through its DHN. However, transitioning to carbon-neutral assets may require additional space in the secondary DHN throughout the city, potentially conflicting with the municipality's goal of maintaining vibrant, green public spaces. EPU has already addressed this issue effectively, as seen with the Rijnsweerd thermal energy storage, which blends seamlessly into its surroundings (Eneco, 2024g). To ensure future success, EPU must continue fostering this collaborative approach to secure necessary building permits and land acquisition.

Grid operators
As mentioned previously, the biggest challenge for grid operators is congestion caused by imbalances between supply and demand. One solution is DSR, which shifts power consumption to periods when supply is abundant. District heating and storage networks support this by storing energy during peak supply hours, thus reducing grid congestion. Furthermore, EPU's power assets, such as LW06, MK12 and the BES system, provide electricity during peak demand, aiding frequency regulation. Additionally, EPU operates one of the Netherlands' four black-start units, enabling power plant restarts during outages. These benefits lay the groundwork for a strong collaborative relationship with grid operators, who may offer tariff discounts in return for EPU's DSR, frequency regulation, and black-start services. Starting in April 2026, the ATR85/15 regulation will come into effect, granting grid operators the authority to limit power delivery for up to 15% of the time to alleviate grid congestion for specific contract forms (Netbeheer Nederland, 2024a). In the event of capacity constraints, operators will provide 24-hour advance notice. Addi-

tionally, this regulation incentivises DSR by offering time-based grid tariff discounts of up to 65%, encouraging flexibility in energy consumption (TenneT, 2024b).

However, EPU's Power-to-Heat assets could contribute to grid congestion during peak thermal demand if it coincides with high power demand. This risk is somewhat mitigated by energy storage, which lowers peak thermal demand.

If EPU plans to increase reliance on P2H in the future, larger grid connections may be required to support distributed P2H assets. Maintaining close collaboration with grid operators and establishing bilateral agreements on capacity and congestion management will be crucial.

Local community

The relationship between the local community and EPU is complex, offering both opportunities and risks that require careful management. While both parties value renewable energy sources, EPU's focus on profitability may conflict with the community's desire for low energy prices. If this pricing risk is left unattended, community members may terminate their DHN contracts and rely on residential P2H technologies, such as e-boilers and heat pumps, leaving EPU with sunk investments. This risk is further exacerbated by the steep price decreases of residential P2H technologies, which are expected to drop by an additional 20-25% by 2030, making the switch away from DHN a financially viable option (Winskel et al., 2024). Additionally, the community values vibrant outdoor spaces, which may conflict with the need for distributed energy assets. EPU can mitigate this by incorporating green walls and biodiversity features, ensuring its assets enhance rather than detract from these spaces. Finally, we identify an opportunity for cooperation through the local community's capacity to invest in photovoltaic (PV) systems and establish local energy initiatives. Power generated from private or community funded renewable energy projects can support EPU's distributed P2H assets. This collaboration is particularly advantageous, as utilizing locally generated power can further help reduce grid congestion.

4.3. SYSTEM DESIGN

The first step in the optimisation of hybrid renewable energy systems is defining the scope of the system design. This includes defining the physical and operational boundaries of the energy system, including thermal and power generation components, and hybrid energy storage systems. Energy Production Utrecht (EPU), a subsection of Eneco, is solely responsible for the operation of the DHN in Utrecht. Unlike their electricity-generating assets, which are dispatched based on their ability to generate profits in electricity markets, the dispatch of thermal assets depends on thermal demand. The thermal demand presents a boundary condition that must always be met. Utrecht's DHN is divided into four districts—Overvecht, Leidsche Rijn, Utrecht City, and Nieuwegein—along with one central production location (EPU). Not all technologies are applicable at each location, making the optimisation more complex and site-specific. As Eneco has committed to achieving carbon neutrality by 2035, the DHN will undergo a drastic shift in terms of energy sources and storage. This optimisation study provides insight into what such a renewable energy system might look like. Consequently, the scope of this optimisation study focuses on EPU's district heating network in 2035.

The objective of this chapter is to provide an answer to sub-research question three and four:

- What system design considerations and trade-offs are important to the energy system in Utrecht?
- Which system components are of importance in Utrecht and what are their dependencies?

4.3.1. ENERGY SOURCES

From the literature it becomes clear that PV and wind power are the most common generation assets, with 52% of studies evaluating a combination of the two (Tahir, 2024). However, equal attention should be paid to alternative energy sources. Especially when considering DHNs, direct thermal energy sources such as geothermal, waste heat, biomass, and solar thermal energy should be considered. Therefore, careful analysis of the applicable energy sources is of imperative importance.

Eneco plans to accelerate the energy transition and fully rely on carbon-neutral energy sources by 2035. By then, LW06 and MK12 will have reached the end of their operational lifetimes, and the BWI is expected to follow suit by 2038. To bridge the gap towards carbon neutrality, Eneco has identified two primary energy solutions along with their anticipated capacities: power-to-heat (P2H) technologies, such as heat pumps and electric boilers, and fuel-to-heat (F2H) options, including CCGTs and peak boilers.(Table 4.1).

Energy source	Expected capacity
LW07	177 MW_e + 136 MW_{th}
Peak boilers	222 MW_{th}
Heat pumps	89 MW_{th}
E-boilers	20 MW_{th}

Table 4.1: The electric (MW_e) and thermal (MW_{th}) capacities of different technologies by 2040

Fuel-to-heat

By 2033, Eneco expects to start the operation of its new CCGT; LW07. Although CCGTs are not inherently renewable or carbon-neutral energy sources, there are several ways in which they can contribute to a renewable energy system. First, it is important to highlight the advantages of CCGTs, which are not only highly efficient but also offer flexibility in dispatch independent from RES. This flexibility allows them to provide heat during periods of insufficient RES production, ensuring a constant and reliable heat supply. The first way a CCGT can be used to contribute to a renewable energy system is by combining it with carbon capture and storage (CCS) technology. In such a setup, LW07 would be carbon neutral regardless of operating on natural gas. The exhaust gases from LW07 would be routed through a CCS plant where greenhouse gasses are removed before entering the environment. Another carbon neutral option is to use blue hydrogen to fuel LW07. Blue hydrogen is made from natural gas in a process called steam reforming. This process releases greenhouse gas emissions which is why the production of blue hydrogen is combined with CCS technology to make it carbon-neutral. It is important to note that, although both options are carbon-neutral, they are not considered renewable as both require natural gas.

A renewable option would be to run LW07 on green gas, which is produced by fermenting organic waste. In coming years, the demand for green fuels, such as green gas and green hydrogen, is expected to increase substantially as decarbonisation efforts intensify (Pöcklhofer, n.d.). However, the production of green gas comes with its own challenges requiring either the production of "energy crops" or wide-spread collection of organic waste. Therefore, demand is expected to outgrow supply, increasing price. Another renewable option is the use of green hydrogen to fuel LW07. However, the production of green hydrogen is currently an inefficient process which makes it costly. Green hydrogen production occurs through electrolysis driven by RES, achieving an efficiency of up to 75% (Mongird et al., 2020). The hydrogen is then compressed in order to be stored, incurring an efficiency loss of up to 30% depending on the level of pressurisation (IEA, 2014). When the hydrogen is used in the CCGT, an additional 15% efficiency loss occurs, resulting in a round trip efficiency of 42%. Fortunately, green hydrogen production is a growing area of interest in the scientific literature, which could increase efficiency and reduce costs in the future. Although multiple options are available, EPU expects to use blue hydrogen, increasing its share in the gas mix by 20% annually from 2035, with the aim of achieving 100% by 2040. LW07 is expected to produce 313 MW_{total} of which 136 MW_{th}.

In addition to primary thermal energy sources, EPU requires peak sources that can be dispatched during abnormal peaks in thermal demand, such as cold winter mornings. EPU expects to have 222 MW_{th} of peak boilers to fulfill such demand. Similar to CCGTs, there are multiple fuel options for these boilers: natural gas in combination with CCS, green gas, blue hydrogen, or green hydrogen. Following a similar schedule to LW07, EPU expects to run its peak boilers on 100% blue hydrogen by 2040.

Power-to-heat

In addition to LW07, eneco expects to supply a significant portion of the thermal demand through P2H, which refers to the direct conversion of electricity to heat. The benefit of P2H is that there are some highly efficient technologies that can use electricity to generate heat and that they can be powered by renewable electricity. The first technology is an electric boiler that uses resistive heating to convert power to heat in a similar fashion to domestic kettles. In such a system, nearly 100% of the energy is converted to heat. Eneco has recently completed the build of two E-boilers with a combined capacity of 20 MW_{th}. Both are expected to continue operations well beyond 2040.

Another important P2H technology is the heat pump (HP). HPs use electricity to transfer thermal energy from one source to another using a refrigeration cycle. HPs are generally not evaluated for their efficiency but rather their coefficient of performance (COP). Most HPs have a COP higher than three, meaning that for each MW_e used, three MW_{th} is transferred into the DHN. Given the remarkable performance of HPs, it is no surprise that EPU is expecting to be heavily dependent on HPs in the future, with 89 MW_{th} coming from a combination of surface water and air-source heat pumps.

Other thermal sources

Currently, EPU operates a biomass plant with an output of 60 MW_{th}. However, biomass is considered a pollutant-heavy fuel with high particulate matter emissions. Operating a biomass plant requires extensive exhaust gas cleaning, which adds operational complexity and increases the spatial footprint of the facility. Additionally, the plant relies on a consistent biomass supply, and currently, only low-quality biomass is available, which further reduces the plant's overall efficiency. Due to these challenges, EPU does not plan to invest further in biomass after the plant reaches its operational end-of-life in 2038. Therfore, biomass as a direct thermal source is not included in the study.

Another potential direct thermal source is waste heat. However, as Utrecht lacks significant industrial activity, the anticipated capacity for waste heat is relatively low. EPU has investigated the feasibility of utilizing two waste heat sources in the future: an asphalt plant and a data centre. However, both options would require substantial investment while providing only 13 and 10 MW_{th}, respectively. Consequently, these projects are unlikely to be realized and are not included in this study.

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Finally, geothermal energy could serve as a valuable direct thermal source. Recent research indicates multiple potential locations within the city of Utrecht where geothermal sources exceeding 5 MW_{th} could be tapped (Böker & Leo, 2021). However, geothermal energy has proven to be a politically sensitive topic. Research into geothermal potential has caused concern within the local community, likely due to fears associated with underground technologies, stemming from the seismic activity linked to natural gas extraction in Groningen. As a result, geothermal energy is unlikely to gain support from the local community and has therefore been excluded from this study.

4.3.2. ENERGY STORAGE

Energy storage plays a crucial role in energy systems by mitigating the intermittency of renewable energy sources, ensuring a consistent and reliable supply. In the literature, BES systems are the most commonly researched with 65% focussing on them. However, scientific interest in hybrid energy storage systems is growing with 29% research focused on hybrid ESS. The growing interest in hybrid ESS is not surprising as implementing a variety of ESS in a multi-storage system enhances system flexibility, reliability, and economy by effectively balancing out the shortcomings of each individual storage technology (Wang et al., 2022). In the literature, the most researched storage technologies are battery energy storage (BES), hydrogen energy storage (HES), thermal energy storage (TES), and compressed air energy storage (CAES). These technologies might offer a good starting point, but more in-depth analysis is required to make an informed decision on a per-case basis.

Thermal energy storage

The most relevant storage technology for EPU is TES as it allows thermal supply and demand to be balanced independent of RES availability. As mentioned in chapter 3, there are many different thermal energy storage technologies, yet not all are suitable for Utrecht's DHN. Only sensible thermal energy storage is currently sufficiently developed and economically competitive for large-scale implementation in district heating networks. For EPU, it is crucial that thermal storage can absorb both short- and long-term energy fluctuations and that the technology is energy-dense to minimise the use of above-ground space, which is scarce in the densely populated city of Utrecht. Furthermore, it is important that the technology can be implemented within the yet existing district heating infrastructure. Based on these requirements, we can conclude that TTES, SSTES, and ATES are suitable for implementation in EPU's district heating network, while MSTES is not. MSTES is designed for shorter storage durations, typically ranging a few hours, which does not provide the dispatch flexibility EPU requires. Additionally, MSTES is best suited for applications focused on power generation rather than direct thermal energy delivery (IRENA, 2020). Among the suitable technologies, ATES is best suited for seasonal thermal energy storage due to its low spatial requirement, high efficiency, and low cost. However, ATES has a slow response time, making it unsuitable for short-term supply and demand balancing. Therefore, ATES must be supplemented with short-term thermal storage options, such as TTES and SSTES (Table 4.2).

Technology	Efficiency	Spatial requirement	Cost
TTES	Middle	Worst	Middle
SSTES	Worst	Middle	Worst
ATES	Best	Best	Best

Table 4.2: The characteristics of different TES technologies in terms of efficiency, spatial requirement, and cost. Best, middle, and worst scores indicate the order among the three technologies.

Battery energy storage

In addition to thermal storage, power storage is another useful technology, as it supports both Power-to-Heat (P2H) applications and power trading. For EPU, BES is the most relevant form of power storage. Although CAES systems have lower investment costs and longer lifetimes than BES, their lower efficiency and energy density make them less favorable for EPU. Typically, CAES systems have a round-trip efficiency of 63%, compared to more than 95% for BES systems (Salvini & Giovannelli, 2022). Furthermore, CAES systems have a volumetric energy density of 11,1 Wh/L, significantly less than the 450 Wh/L offered by BES systems (Gao et al., 2023; Office of energy efficiency and renewable energy, 2022).

Hydrogen Energy Storage (HES) systems are another promising power storage technology. HES is particularly relevant for long-term power storage when used in combination with BES for short-term balancing (Li et al., 2023). However, HES systems typically have lower roundtrip efficiencies, around 35%, and higher investment costs, approximately \$349 per kWh (Mongird et al., 2020). In contrast, BES systems have efficiencies of over 95% and lower costs, around \$156 per kWh (BNEF, 2023). Because long-duration thermal energy storage can be achieved more efficiently and affordably with ATES, and short-term power storage can be achieved more efficiently and affordably with battery storage, HES has not been included in this study.

4.3.3. SYSTEM CONFIGURATION

The discussed energy sources and storage technologies are integrated to provide thermal energy to all 55,000 households connected to EPU's district heating network. This study will consider two slightly different configurations of the DHN.

GridSync configuration

During real-world operations, Power-to-Heat (P2H) and Battery Energy Storage (BES) assets are not directly linked to photovoltaic (PV) or wind parks but are instead connected to the power grid. Consequently, the levelised cost of power for these assets is not determined solely by production costs; it is also subject to the dynamics of fluctuating market prices. To address this, the study employs a system design referred to as the GridSync (GS) configuration, which will serve as the foundation for this research.

In the GridSync configuration, thermal energy is supplied either directly by the Combined Cycle Gas Turbine (CCGT) or through peak boilers. Alternatively, thermal energy can be generated via P2H assets, which use electricity sourced from the CCGT or purchased from the power grid. This thermal energy can then be stored in one of the thermal energy storage systems or directly utilised to meet demand. Additionally, electricity generated by the CCGT can be stored in the BES system, enabling it to power the P2H assets at a later time. The BES system also participates in energy trading by charging during periods of low power prices and discharging during periods of high prices. Similarly, the CCGT has the capability to sell surplus power directly to the electricity market. (Figure 4.2).

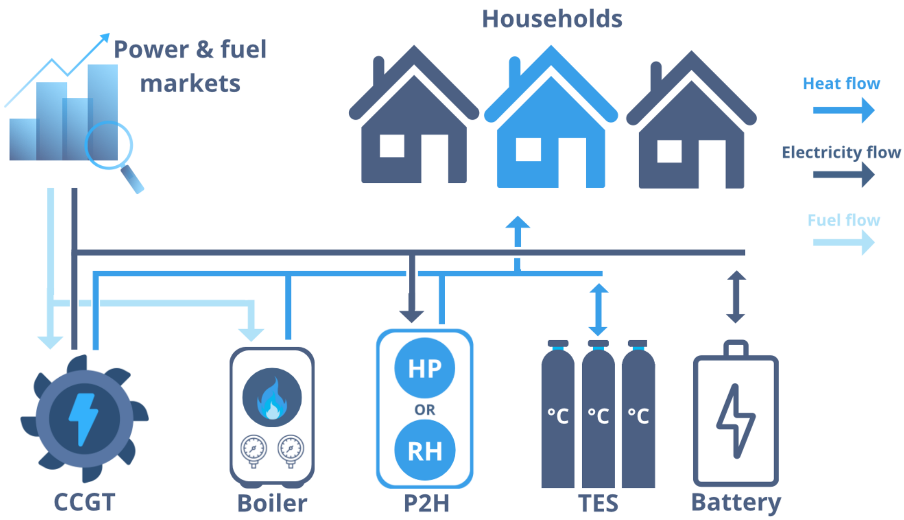

Figure 4.2: An overview of the GridSync configuration, which incorporates power markets through the power grid, waste heat, a combined cycle gas turbine, power-to-heat assets such as heat pumps and resistive heating, thermal energy storage, peak boilers, and a battery.

EcoPure configuration

The EcoPure (EP) design is similar to the GridSync design, with one key difference: instead of sourcing electricity from the power grid at market prices, it relies solely on

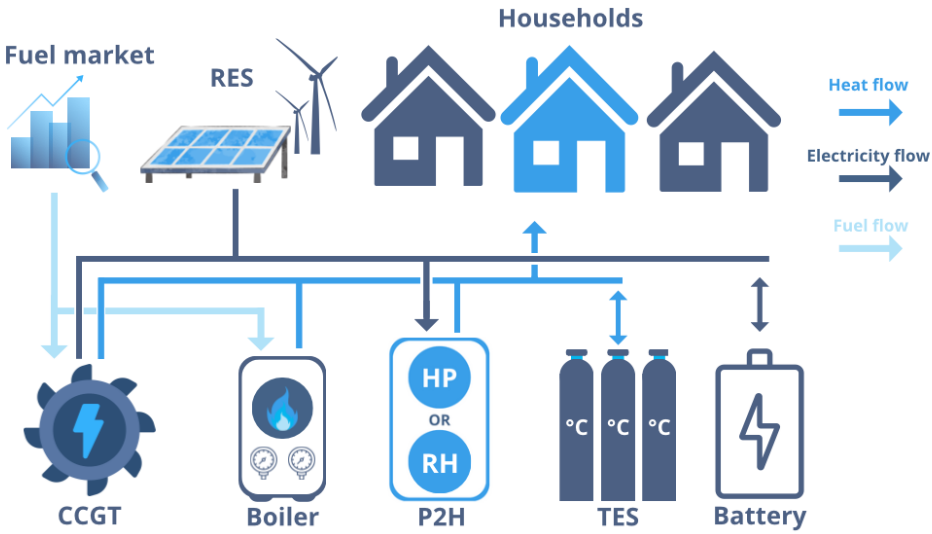

Figure 4.3: An overview of the EcoPure system configuration, which incorporates renewable energy sources, power-to-heat assets such as heat pumps and resistive heating, thermal energy storage, peak boilers, CCGTs, and a battery.

variable renewable energy sources, specifically solar and wind. This means that the availability of power for the system depends entirely on the output of these renewable sources. If solar and wind generation drop to zero, no power is available to run the system. This setup aims to demonstrate how EPU's District Heating Network (DHN) could function if it relied exclusively on renewable power, highlighting the challenges and requirements of such a transition. Flexible CCGTs and peak boilers are included as backup options to ensure reliability when renewable energy is insufficient (Figure 4.3).

4.3.4. SPATIAL DESIGN

As mentioned previously, EPU's district heating network is divided into four districts: Nieuwegein, Utrecht City, Leidsche Rijn, and Overvecht. Currently, each district is supplied by thermal energy from EPU, supplemented by distributed auxiliary plants. One direct primary connection runs from EPU to Nieuwegein (175 MW), with branches to Leidsche Rijn (110 MW) and Utrecht City (130 MW), along with direct primary connections to Utrecht City (130 MW) and Overvecht (130 MW). Finally, there is a connection from Overvecht to Utrecht City with a capacity of 130 MW (Figure E.2). These are one-way connections with fixed capacities determined by pipe diameter and pump speed.

Within EPU's district heating network, not all technologies are applicable to all locations. The primary factor determining applicability is whether it concerns the primary grid (EPU) or the secondary grid (the four districts). At EPU, all energy sources are available, though not all storage technologies are feasible. The primary grid transports water at 120°C, making atmospheric TTES unfeasible.

Conversely, secondary locations have access to all above-ground storage technologies, but not all energy sources are available and neither is ATES. CCGTs require both extensive fuel infrastructure and large power grid connections. Currently, EPU is the only suitable location, satisfying both requirements. Technically, both E-boilers and heat pumps can be installed at secondary locations. However, heat pumps are more suited for distributed thermal sources due to their higher thermal output relative to grid connection requirements. Heat pump installations, however, are large and require spatial analysis near heat transfer stations, which is currently unavailable. Therefore, in the model, all P2H assets are located at EPU. Additionally, since ATES requires a heat pump to function optimally due to the secondary grid's temperature fluctuations (72-92°C), this technology is also limited to EPU. For Eneco, the BES' primary use case in Utrecht is to store power in order to supply the P2H assets. Therefore, BES is only placed at locations with P2H assets. Finally, peak boilers are available at all secondary locations except for Leidsche Rijn which does not have a gas supply at the heat transfer station (Table 4.3).

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Location	CCGT	peak boiler	P2H	TTES	ATES	SSTES	BES
EPU	X	X	X	-	X	X	X
Nieuwegein	-	X	-	X	-	-	-
Leidsche Rijn	-	-	-	X	-	-	-
Overvecht	-	X	-	X	-	-	-
Utrect city	-	X	-	X	-	-	-

Table 4.3: The placement of technologies across different DHN locations. X shows that a technology is present at the corresponding location.

4.4. OPTIMISATION DESIGN

This chapter provides a comprehensive overview of the core components that shape the optimization process: decision variables, objectives, and the optimization algorithm. This chapter delves into the critical aspects of how these elements interact to achieve optimal solutions. We begin by exploring the decision variables, which represent the adjustable parameters within the model that drive the optimization outcomes. Next, we define the objectives, which establish the goals of the optimization, such as minimizing cost or maximizing efficiency. Finally, we discuss the optimization algorithm, the computational method used to navigate the complex landscape of potential solutions and identify the optimal set of decision variables. Together, these components form the foundation of our optimization approach, guiding the model towards achieving the desired outcomes efficiently and effectively.

The objective of this chapter is to provide an answer to sub-research question one and two:

- What decision variables and objectives are identified in the literature and what are the trade-offs between them?

- Which optimisation algorithms or combination of algorithms are identified in scientific literature and what insights do they provide?

4.4.1. DECISION VARIABLES

In optimization, decision variables are the key elements that determine the outcome of the optimization process. They represent the choices or quantities that can be adjusted within the model to achieve the desired objective, such as minimizing cost or maximizing efficiency. The values of these variables are not fixed but are instead determined through the optimization process, guided by the objective function and subject to a set of constraints. In this chapter, we will explore the specific decision variables used in our model, detailing their roles and how they interact to influence the overall system performance. Understanding these variables is crucial for comprehending the optimization strategy and its practical implications in the context of the problem at hand.

From the literature, we can identify three primary categories of decision variables. Most optimisation studies in renewable hybrid energy systems optimise the capacity of system components (Literature review). However, some studies also focus on the optimisation of the dispatch strategy or network analysis, optimising the location of assets in the DHN. Component capacity emerges as the most relevant decision variable for EPU given their commitment to achieving net zero emissions. This means that for energy sources their energy capacity in kW is optimised while for storage technologies both the energy capacity in kW and storage capacity in kWh are optimised. Such optimization of component capacity is crucial as it addresses the fundamental aspect of how a renewable energy system could be structured and operated effectively. The uncertainty surrounding the practical and cost-effective implementation of such systems makes it important to focus on accurately sizing system components. This ensures that energy production not only aligns with sustainability goals, but also remains economically viable. Understanding the optimal capacity needed for each component will help EPU navigate the complexities of transitioning to a renewable infrastructure while balancing cost, efficiency, and reliability.

4.4.2. OBJECTIVES

From the literature review (Chapter 2), we can identify three primary objectives for optimisation in energy systems: cost, emissions, and reliability. Although, for each of these objectives, there are multiple key performance indicators which can be optimised, there are some industry standard measures. Cost is most often assessed based on the levelised cost of energy (LCOE) which takes both capital expenditures and net present operational expenditures into account to calculate a per-unit energy cost:

$$LCOE = \frac{\sum_{t=1}^{n} \frac{I_t+M_t+F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}} \tag{4.1}$$

Where I_t is the investment cost in year t, M_t the maintenance cost in year t, F_t the fuel cost in year t, E_t the energy delivered in year t, and r the discount rate.

According to T. Liu et al. (2022), the reliability of an energy system is commonly measured by the loss of power supply probability (LPSP). LPSP is a measure used to quantify the reliability of a power supply in meeting load demands. It refers to the fraction of total demand that remains unmet within a specified time period. Essentially, LPSP represents the percentage of time the power supply does not meet load demand, indicating the reliability of the system to maintain power supply.

$$LPSP = \frac{\sum_{t=1}^{n} |\min(0, S_t - D_t)|}{\sum_{t=1}^{n} D_t} \tag{4.2}$$

Where S_t is the power supply and D_t is the demand at time t.

Finally, the environmental impact of an energy system is most commonly measured in carbon dioxide (CO_2) equivalent greenhouse gas emissions. This metric takes into account not only CO_2 but also other greenhouse gases such as methane (CH_4), converting their impact into a CO_2-equivalent value based on their global warming potential. By using CO_2 equivalents, we can provide a comprehensive assessment of the total greenhouse gas emissions associated with an energy system, facilitating better comparisons and decision-making regarding sustainability and environmental responsibility.

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Multi-objective optimization involves optimizing two or more conflicting objectives simultaneously, which can be complex and computationally intensive. This complexity can be transformed into a simpler single-objective optimization problem by formulating some of the objectives as constraints. In this approach, also known as the ε-constraint method, one primary objective is selected for optimisation, while the other objectives are converted into constraints with acceptable threshold values (Nikas et al., 2022). For example, in an energy system design, minimising cost could be the primary objective, while emission levels and energy security are treated as constraints that must not exceed certain limits. This transformation simplifies the optimization process, making it computationally less demanding and easier to solve using traditional single-objective optimization techniques. The benefits of this method include reduced computational resources, a clearer focus on the most critical objective, and simpler interpretation and implementation of results (Nikas et al., 2022).

Instead of treating cost, emissions, and energy security as separate objectives, the demonstrated optimization will focus on minimizing cost while converting emissions and energy security into constraints, thereby implementing the ε-constraint method. Given Eneco's commitment to achieving climate neutrality by 2035, the design space has been limited to sustainable energy assets only, ensuring that all solutions align with this environmental goal (Chapter 4.3.3). Additionally, since the loss of energy supply would mean that customers would not be able to heat their homes, a crucial constraint will be that supply must always exceed demand. By prioritising cost reduction within these strict sustainability and security parameters, we aim to develop an efficient, environmentally friendly, and dependable DHN for Utrecht.

The total cost of an asset over its lifetime consists of two components: capital expenditures (CAPEX) and operational expenditures (OPEX). CAPEX can be defined as:

$$CAPEX = c_a I_{c,a} + v_a I_{v,a} \tag{4.3}$$

Where c_a is the energy capacity of asset a in kW, $I_{c,a}$ the investment cost of each unit of energy capacity for asset a, v_a is the storage capacity of asset a in kWh, and $I_{v,a}$ is the investment cost of each unit of storage capacity for asset a.

The OPEX over the lifetime of an asset is the net present value of all O&M expenditures and can be defined as:

$$OPEX = \sum_{t=1}^{n} \frac{f_a CAPEX + b_{a,t} - R_{a,t}}{(1+r)^t} \tag{4.4}$$

Where f_a is a factor which expresses O&M expenditures as a percentage of CAPEX for asset a, $b_{a,t}$ is the fuel cost of asset a at time t, $R_{a,t}$ is the revenue generated by asset a at time t, and r is the interest rate.

The objective of the optimisation is to minimise the total cost across all assets and can be described as:

$$\text{Minimize} \sum_a \left(c_a I_{c,a} + v_a I_{v,a} + \sum_{t=1}^{n} \frac{f_a(c_a I_{c,a} + v_a I_{v,a}) + b_{a,t} - Ra,t}{(1+r)^t} \right) \tag{4.5}$$

Subject to:

$$0 \le c_a \le c_{a,\max} \quad \forall a \in \{1,2,\ldots,a\}$$
$$0 \le v_a \le v_{a,\max} \quad \forall a \in \{1,2,\ldots,a\}$$
$$S_t \ge D_t \quad \forall t \in \{1,2,\ldots,T\}$$

Where $c_{a,\max}$ is the maximum energy capacity of asset a, $v_{a,\max}$ is the maximum storage capacity of asset a, D_t is the total thermal energy demand at time t, and S_t is the total thermal energy supply at time t defined by:

$$S_t = \sum_a p_{th,t,a} \tag{4.6}$$

Where $p_{th,t,a}$ is the thermal energy production of asset a at time t.

Trade-offs
When discussing the optimization objectives, we can identify some clear interdependencies and trade-offs between cost, emissions, and reliability. These objectives are often in tension with one another, requiring careful balancing to achieve an optimized energy system.

1. Cost & Emissions: Minimizing costs often involves trade-offs with emissions, as lower-cost options may include fossil-based generation that increases carbon output. In contrast, while renewable energy sources reduce emissions, they often require higher upfront capital investments and introduce variability due to their dependence on weather conditions, such as wind and sunlight. This variability necessitates costly energy storage solutions to ensure a stable energy supply.

2. Reliability & Emissions: Ensuring a reliable supply of energy may sometimes require fossil-based backup systems that can quickly ramp up in response to demand. Renewable sources, though lower in emissions, may not always provide sufficient reliability due to their intermittent nature. As a result, achieving high reliability while minimizing emissions is challenging without substantial storage or flexibility options, which themselves impact costs.

3. Cost & Reliability: While minimizing costs is desirable, maintaining high reliability often requires additional investments in backup capacity or energy storage. Redundancies and storage systems that improve reliability can significantly increase both CAPEX and operational expenses. Thus, reducing costs can lead to reduced reliability if the system lacks sufficient backup or flexibility to handle demand fluctuations.

Therefore, the presented optimization, with constraints on emissions and reliability, will inherently result in higher total system costs compared to a system with more relaxed emissions and reliability requirements.

4.4.3. OPTIMISATION ALGORITHM

There are two general approaches to optimization in energy systems: single- layer optimization and two-layer optimisation. In the two-layer method, sizing and operational dispatch optimizations are conducted sequentially using heuristic algorithms (Huang et al., 2024). The most frequently used heuristics are Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) due to their favourable trade-off between solution time and performance (Tahir, 2024).

Genetic algorithms are powerful evolutionary optimization techniques that mimic natural selection (McCall, 2005). They are widely used to find near-optimal solutions within complex optimization problems where traditional methods may struggle due to the computational complexity (McCall, 2005). According to McCall, GAs initiate with a randomly generated population of candidate solutions, referred to as individuals. These individuals are iteratively improved through a predefined number of iteration cycles. Each individual possesses unique 'genes,' which represent different configurations of decision variables. During each iteration, the performance of each individual is evaluated based on the objective function, with those showing the highest fitness values selected for reproduction. Consequently, better-performing individuals have a higher probability of progressing to subsequent generations. During reproduction, selected individuals exchange genetic information through a process called crossover, analogous to biological reproduction, allowing the algorithm to efficiently navigate undiscovered areas of the solution space. Additionally, the population undergoes mutations, which help maintain diversity and prevent premature convergence on local optima (2005).

The benefit of GAs is that they can handle complex, non-linear, and non-convex optimisation problems with multiple local optima (Biswas, 2022). Furthermore, they are computationally efficient as they can explore large solution spaces efficiently and they are parallelizable further reducing the solution time for complex models (Biswas, 2022). However, the implementation of GAs does not guarantee finding the local optimum and does not allow for the simultaneous optimisation of dispatch strategy.

Similar to GAs, PSO is a meta heuristic inspired by nature. It simulates the social behaviour of bird flocking, with each candidate solution represented as a particle navigating the solution space (Wahab et al., 2015). The particles explore the solution space by adjusting their positions according to the most optimal position they have individually discovered and the most favourable position identified by the swarm as a whole. According to Gad (2022), PSO has several advantages, including simplicity, ease of implementation, quick solution time, and the ability to handle non-convex and non-linear optimization problems. However, PSO can get stuck in local optima and may face challenges with high-dimensional optimisation problems. (Chun-Wei Lin et al., 2024).

Conversely, the single-layer method integrates sizing and operational dispatch optimization, using Mixed-Integer Linear Programming (MILP) to achieve globally optimal solutions based on real-time and forecasted data. This method treats both size and operational parameters as variables optimized concurrently, often resulting in better performance. However, computational challenges may arise with increasing constraints and timeseries data, requiring the use of clustering techniques like k-means to manage computational loads effectively. This approach strives to balance computational efficiency with solution accuracy in complex, hybrid energy systems (Huang et al., 2024).

For EPU, the system optimisation will be performed to determine the optimal size of system components. Consequently, the storage capacity of storage technologies and energy capacity of energy sources will be optimised to achieve the lowest overall system costs. Due to the large number of system components and their complex dependencies and interactions, a rule-based asset dispatch approach is unlikely to accurately reflect optimal system operations. Therefore, a two-layer optimisation approach would most likely deviate significantly from the global optimum making a single-layer optimisation using MILP more appropriate. However, the proposed system design integrates both short- and long-term energy storage necessitating the implementation of extensive time series data to accurately reflect seasonal energy flows. Combined with the extensive constraints required for modelling system behaviour, this makes solving the problem computationally expensive. Therefore, the proposed single-layer approach might require techniques to alleviate some of the computational complexities.

4.5. MODEL DEVELOPMENT

In this chapter, we delve into the development of a comprehensive model for a Hybrid Renewable Energy System in Utrecht. This involves a detailed examination and modeling of each component within the system, ranging from generation units such as solar, wind, and CCGTs, to various storage systems including batteries and thermal storage, and finally, the load profiles that these systems aim to support.

Accurate modeling and simulation of an HRES require specific data inputs. We will begin by specifying the necessary data such as historical RES patterns, load demands, and cost details, which are crucial for realistic simulations and forecasting. Understanding these requirements helps in designing a model that not only reflects theoretical capabilities but also practical viability.

Furthermore, we will develop detailed models for each system component. This involves understanding the individual characteristics and performance metrics of generation and storage units, as well as how these components can be optimised for cost efficiency.

4.5.1. DATA REQUIREMENTS

The model requires five primary input datasets. In this section, we will first discuss three datasets concerning renewable generation profiles, followed by consumption data, and finally, data on power markets.

Power generation

The three generation datasets from the National Energy Dashboard (NED) show the aggregate energy production from PV, onshore, and offshore wind energy in the Netherlands for 2023. (NED, 2024). In order to use the data in the model, each of these datasets has been pre-processed to show generation in kWh per m2. From the generation profiles, it becomes apparent that a combination of PV and wind provides a well-distributed energy generation throughout the year. Photovoltaic power tends to peak in the summer due to high solar irradiance, while wind power peaks in the winter when PV generation is at its lowest (Figure 4.4).

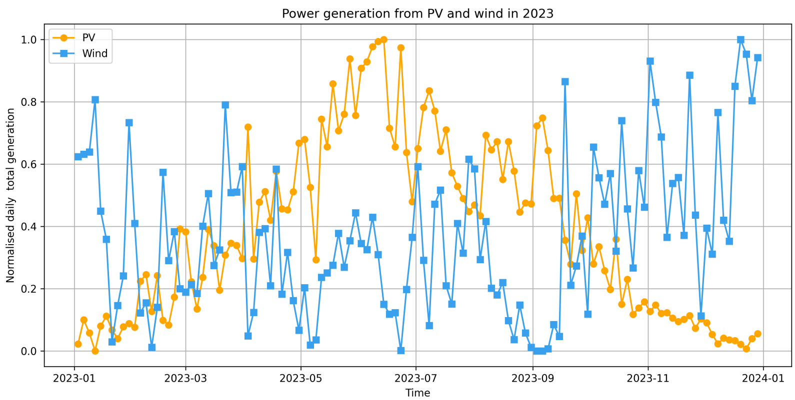

Figure 4.4: Daily normalized total power generation from wind and PV, 2023.

Furthermore, the data indicates that both the offshore and onshore wind profiles are very similar (Figure A.2 & A.3). However, offshore wind generally generates more power compared to onshore wind. Specifically, onshore wind generates an average of 0.10 kW per m^2, while offshore wind produces an average of 0.12 kW per m^2. This difference is statistically significant, with a p-value smaller than 0.01. Similarly, the complementary nature of PV and wind observed in their annual generation profiles extends to daily fluctuations. While PV power typically peaks around noon and operates only during sunlight hours, wind energy offers a more consistent output across the entire day (Figure A.4). This variation showcases the benefits of diversifying across multiple renewable energy sources.

Thermal demand

In addition to generation profiles, the model requires thermal demand data for EPU's district heating network. Due to the Dutch climate, thermal demand varies significantly across seasons. During winter, thermal demand surges and becomes highly volatile as outside temperatures drop. In contrast, during summer, thermal demand stabilizes at a much lower level (Figure 4.5).

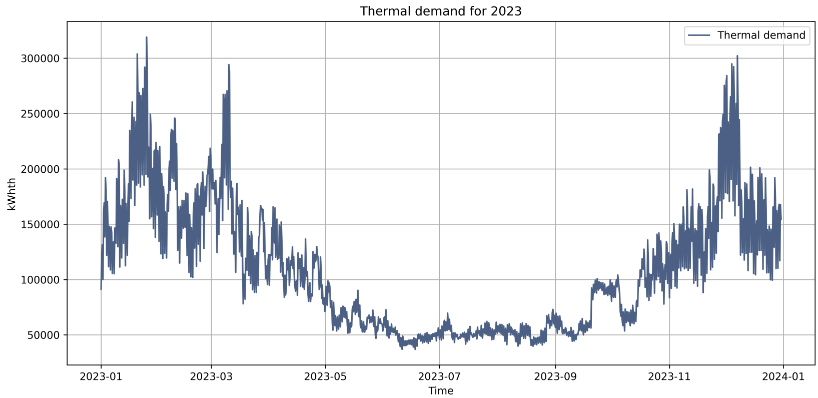

Figure 4.5: Hourly Thermal Demand Averaged Over 8-Hour Intervals in kWh_{th}, 2023.

From May until October, the mean thermal demand is 57.511 kW, with lows and highs reaching 33.188 kW and 130.000 kW, respectively. Conversely, from November until April, the mean thermal demand is 147.617 kW, with lows and highs reaching 51.158 kW and 346.330 kW, respectively. On a daily timeframe, thermal demand typically peaks in the morning between 7 and 9 AM, presumably due to space heating and hot water usage. After this morning peak, thermal demand decreases to a baseline level throughout the day, then rises again in the evening between 5 and 8 PM. Following the evening peak, demand gradually decreases, reaching its lowest point after midnight (Figure A.5). Utrecht's DHN is divided into four districts: Nieuwegein, Utrecht city, Leidsche Rijn, and Overvecht. According to Eneco, Utrecht city accounts for 52% of the total demand, Leidsche Rijn for 19%, Nieuwegein for 18%, and Overvecht for 11% (Eneco, 2024b). Consequently, the demand dataset has been split into four subsets to represent the demand for each district.

Power market

As mentioned in chapter 4.3.3, EPU's power-to-heat assets are connected to the power grid. Therefore, the cost of thermal energy is partly dependent on market prices for electricity. These market prices are dependent on supply and demand and can be highly volatile accross multiple different markets. One such example of a power market is the imbalance market which is used to balance power supply and demand on a minute-by-minute time frame. Another market is the automatic frequency restoration reserve (aFRR) which is used to maintain the 50 Hz frequency of the Dutch power grid (Tennet, 2022). It is in these markets where DHSNs can participate to actively balance supply and demand. During periods of excess power generation, power prices on the imbalance and aFRR market can become deeply negative. In such periods, P2H and BES assets can be used to respectively generate heat or store electricity. If such a drop in power prices does not coincide with thermal demand, the thermal energy from P2H assets can be stored in the various TES technologies. Conversely, when power prices increase due to a lack of supply or a surge in demand, BES systems can profit by selling their power back to the grid. However, the small time frame and high volatility of these markets make it impossible to forecast long term power prices. A more stable power market is the day-ahead market. The day-ahead market operates via a blind auction conducted once daily to determine the hourly power prices for the next day based on supply and demand forecasts (EEX Group, 2024). Therefore, similarly to the imbalance markets, day-ahead prices fluctuate throughout the day. However, prices are not affected by short term power imbalances as they are fixed on an per-hour basis. Although it seems unintuitive due to their scheduled nature, day-ahead prices can still turn negative as a result of supply and demand imbalances. This can be caused by high RES feed-in or inflexible power sources such as nuclear plants (EEX Group, 2024). Due to the larger time frames and more predictable nature of day-ahead prices, Eneco has developed day-ahead forecasts based on various scenarios, which we will incorporate into the optimization model. These forecasts are based on three scenarios: global transition, local independence, and stated pledges.

Global transition scenario

The Global Transition (GT) scenario envisions a pathway to carbon neutrality by 2050, with an Intermediary goal of at least a 55% reduction in emissions by 2030 (Entsog & Entso-e, 2022). This scenario emphasizes the deployment of diverse renewable and low-carbon technologies, many of which are centralised, alongside the use of global energy trade to accelerate decarbonisation. Economies of scale drive large cost reductions in renewable technologies, while the import of decarbonised energy from cost-effective sources is also seen as a practical approach (Entsog & Entso-e, 2022).

Local independence scenario

The Local Independence (LI) scenario envisions a pathway to carbon neutrality by 2050, with an Intermediary goal of at least a 55% reduction in emissions by 2030 (Entsog & Entso-e, 2022). This scenario is propelled by societal commitment to attaining energy self-sufficiency through abundant local renewable energy sources. It reflects a shift in lifestyle and a decentralized push for decarbonization, driven by initiatives from citizens, communities, and businesses, with support from authorities. As a result, renewable energy production in Europe is maximized, and energy imports are significantly reduced (Entsog & Entso-e, 2022).

Stated pledges scenario

The Stated Pledges (SP) scenario describes a pathway aligned with national energy and climate policies that are based on European targets, aiming to achieve carbon neutrality by 2050 and a 55% reduction in emissions by 2030 (Entsog & Entso-e, 2022).

The three price curves are generated by a complex model that considers historical weather patterns, projected renewable energy share, fossil fuel prices, and power demand. The SP scenario exhibits the highest reliance on renewable energy sources, with 123 GW sourced from solar and wind. In comparison, the LI and GT scenarios are forecasted to have 108 GW and 79 GW, respectively (Table 4.4).

Scenario	Solar capacity	Wind capacity	Total
Global transition	50.78	27.77	78.55
Local independence	73.71	34.55	108.26
Stated pledges	84.41	38.96	123.37

Table 4.4: The installed renewable energy capacity in GW for solar power, wind power, and combined total

None of the scenarios predict negative power prices in 2035, underscoring the improved grid balance achieved through energy storage and demand-side response mechanisms. However, power prices in 2035 still exhibit the expected volatility and patterns associated with an increasing reliance on renewable energy. On average, power prices are at their lowest from 7:00 AM to 4:00 PM across all three scenarios, due to high solar production (Figure: 4.6). Unsurprisingly, the average daily prices for the SP scenario are the lowest, as this scenario has the highest total renewable capacity.

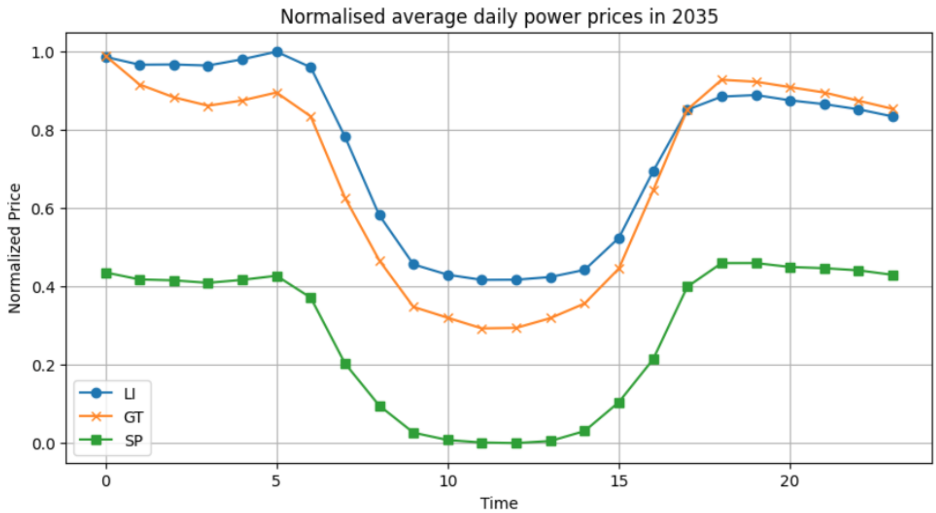

Figure 4.6: Normalised average daily power prices for 2035 across all scenarios

Similarly, the fluctuations observed in daily power prices extend to annual fluctuations. Average weekly power prices reach their lowest during the summer months, when solar irradiance is at its peak, and climb higher during the winter, when the installed solar capacity produces less energy (Appendix A.6). However, due to the combination of solar and wind power, power prices still reach lower points during winter, offering strategic opportunities for energy storage systems to charge.

Fuel markets

In addition to the power market, the fuel markets play a critical role in EPU's operations. This research focuses on two key fuel markets: Hydrogen (H_2) and Natural Gas (NG). Both fuels are utilized by the CCGT and peak boiler technologies for heat and power generation.

Similar to the power market, fuel prices fluctuate based on the time of consumption, though price volatility in these markets tends to be less pronounced. The price of blue hydrogen is determined on an hourly basis and has been forecasted by Eneco for 2035, with an average projected cost of 11.5 cents per kWh (Figure A.7).

In contrast, natural gas is not carbon neutral, which necessitates the purchase of EU Emission Trading System (ETS) credits. ETS is a cap-and-trade system which limits the total amount of emissions that can be produced by an industry (European Commission, n.d.). Companies are allocated or must purchase ETS credits, each representing the right to emit one tonne of CO_2 equivalent emissions. Currently, the cost of ETS credits is around €70 per tonne of CO_2, with prices expected to remain stable until 2030, before rising to approximately €100 per tonne by 2035 as regulations become stricter (Enerdata, 2023). It is important to note that purchasing carbon offsets does not exempt companies from ETS obligations since 2020 (European Commission, 2021). ETS credits must still be acquired to cover the generated emissions.

4

To calculate the necessary adjustments for natural gas prices, we first established a baseline using historical data. The NG price profile was calculated as the monthly median from January 1990 to September 2024 (FRED, 2024). The median provides a more accurate representation of typical NG price trends by smoothing out the impact of abnormal price spikes, such as those caused by the Russia-Ukraine war. The historical mean price over this period is €0.016 per kWh.

Looking ahead, the International Energy Agency (IEA) projects NG prices to range between \$4.3 and \$6.9 per MMBtu across three different scenarios for 2030, with a median expectation of \$6.5 per MMBtu, which equates to approximately €0.022 per kWh (IEA, 2023). As a result, the historical NG price profile has been adjusted to align with these future projections.

Natural gas used in the Netherlands results in 2.085 kg of CO_2 equivalent emissions per m^3 (Anthesis, 2023). Given that natural gas produces 9.77 kWh of energy per m^3, this equates to approximately 0.21 kg of CO_2 emissions per kWh of natural gas consumed. In addition to purchasing ETS credits, Eneco can utilize the carbon offset market to neutralize the carbon footprint associated with natural gas consumption and achieve CO_2 neutrality. Bloomberg identifies three potential scenarios for the development of the carbon offset market, each with varying prices and dynamics.

Voluntary market scenario

In this scenario, the supply of carbon offsets is projected to be nearly four times greater than demand, resulting in a low price of just \$13 per ton and valuing the market at a modest \$15 billion by 2030. By 2035, the price is expected to rise to \$18 per ton, and by 2050, it is projected to reach \$35 per ton. This situation presents a significant challenge for the market: the abundance of cheap, low-quality offsets could discourage critical investment in high-integrity solutions, such as direct air capture (DAC), ultimately impeding progress toward meaningful emissions reductions (Bloomberg, 2023). In this scenario, the average NG price throughout the year would be €0.047 per kWh.

Bifurcation market scenario
In this scenario, the carbon offset market is likely to split into two segments once stakeholders establish a definition for “high-quality” offsets. A smaller, less liquid market for high-quality offsets would emerge, with prices peaking at $38 per ton in 2038, though still insufficient to drive investment in technology-based removals like DAC. Meanwhile, a larger, low-quality market would persist, with prices reaching only $22 per ton by 2050, exacerbating existing issues in today’s market (Bloomberg, 2023). In this scenario, Eneco would opt for high-quality carbon offsets to stay aligned with their sustainability goals, with costs expected to reach $37 per ton by 2035 (Bloomberg, 2023). This choice reflects a commitment to higher standards, even as the market for low-quality offsets remains cheaper, reinforcing Eneco’s focus on integrity and meaningful carbon reduction. In this scenario, the average NG price throughout the year would be €0.051 per kWh.

Removal market scenario
In a removal-focused scenario, offset prices would gradually rise to new highs, allowing buyers time to adapt. This market, centeres entirely on carbon removals such as reforestation, agriculture, and direct air capture (DAC) (Bloomberg, 2023). The removal-only market keeps supply and demand in a tight balance until 2050, with a brief period of undersupply from 2037 to 2044. Prices would climb to $42 per ton by 2030, spike to $195 per ton in 2035, and $254 per ton by 2037, before settling at $95 per ton in 2050. On average, the price per ton is projected to be $127, which is used as the basis for this scenario (Bloomberg, 2023). In this scenario, the average NG price throughout the year would be €0.068 per kWh.

Data shifting
It is crucial that the optimization accurately reflects the seasonal energy flows within the system. Typically, seasonal thermal energy storage is charged during the summer months, when thermal demand is at its lowest and power generation from PV is at its highest, and discharged during the winter. To capture this behavior in the model, all datasets are adjusted to start in May and end in April.

4.5.2. MODELLING OF SYSTEM COMPONENTS
The optimization model presented in this research was created using Python, with Calliope — a free and open-source Python library designed to model energy systems. Calliope "focuses on flexibility, high spatial and temporal resolution, the ability to execute many runs based on the same base model, and a clear separation of framework (code) and model (data). Its primary focus is on planning energy systems at scales ranging from urban districts to entire continents. In an optional operational mode it can also test a pre-defined system under different operational conditions" (Calliope, 2023). Additionally, Calliope (2023) supports *modeling to generate alternatives* (MGA). MGA emphasizes generating alternatives that vary widely while staying within a predefined range from the optimal objective outcome.

Calliope utilizes the widely adopted Pyomo optimization package as its back-end but organizes the coding process into a more intuitive structure. In Calliope, each asset is categorised as a "technology," which is further divided into four types: supply, transmission, conversion, and storage. Supply technologies draw resources from outside the system and convert them into energy carriers, such as power or heat. Transmission technologies are responsible for transporting energy from one location to another. Conversion technologies transform one type of energy carrier into another, and storage technologies store a predefined energy carrier for later use. The technology class and energy carrier determine the logic governing the energy flow between different assets. Power from a supply technology can only be transferred to assets that accept power as their input, such as power storage or P2H conversion technologies. Similarly, heat can only be directed to assets that accept heat as their input, such as thermal storage or demand. More generally, the output carrier of a given technology can only be transferred to another technology that accepts the same carrier as its input (Figure E.1).

Photovoltaic
PV technology is used in the EP configuration and is defined as a supply technology. It utilizes the PV generation profile dataset as its resource, converting this into the power carrier within the model. The primary objective of the EP system design is to determine the required RES and storage capacity needed to operate Utrecht's DHN entirely on renewable power. Consequently, the maximum PV capacity and available physical area are not constrained.

To connect PV power to the grid, the direct current (DC) must first be converted to alternating current (AC) by an inverter. These inverters typically achieve efficiencies between 95.5% and 98.5% (Grab et al., 2022). In the optimization model, the inverter loss is assumed to be 3%, corresponding to an efficiency of 97%. Recent research indicates that the economic lifespan of PV systems ranges from 15 to 20 years. As noted by Tan et al. (2022), photovoltaic modules typically have a technical lifespan of 25 years, based on performance warranties guaranteeing 80% of the initial peak capacity after 25 years of use. However, factors like "climate conditions, societal behavior, fiscal policies, and technological advancements" can result in earlier replacement (Tan et al., 2022). Therefore, the economic lifespan of PV panels in the model is set to 20 years.

In addition to these technical characteristics, the model also considers the costs associated with PV. Currently, the capex of fixed-axis PV sits at €616 per kW (BNEF, 2023). However, it is expected that this will drop to \$440[1] per kW in 2035 (BNEF, 2023). Annual Operational and Maintenance (O&M) expenditures are generally 1.1% of capex for PV (Ramasamy et al., 2021). The discount rate for all technologies including PV is set to 9%, Eneco's standard rate. In the model, PV is not able to export its power as it can produce electricity cheaper than market prices, making the optimisation unbounded.

Wind turbines
Wind turbines are another technology used in the EP configuration, and are defined as a supply technology. There are two different instances: offshore and onshore turbines.

[1] All dollar values have been converted in the model to euros using the exchange rate of 1.09 EUR/USD as of 16 October 2024.

Each instance uses its own dataset as a resource, which is then converted into the power carrier within the model. Similar to PV, there is no constraint on the maximum capacity for both onshore and offshore wind power. Like PV, wind turbines generate DC power, which needs to be converted to AC before being fed into the grid. The inverter loss is assumed to be 3%, corresponding to an efficiency of 97%. The industry-standard lifetime assumption for wind turbines is typically between 20 and 25 years. However, in practice, offshore wind turbines can last up to 35 years once operational, and onshore wind turbines can also exceed a lifespan of 30 years (Bills, 2021). To remain close to industry standards, we assume the lifespan of both onshore and offshore wind turbines to be 25 years. While onshore and offshore wind power are similar in terms of technical characteristics, they exhibit significant financial differences. In 2022, the total capex for onshore wind was $1750 per kW, whereas offshore wind had a considerably higher capex of $2700 per kW (BNEF, 2023; Stehly et al., 2023). The capex for offshore wind is expected to drop by 1.09% anually until 2028 (BNEF, 2023). Assuming the same cost reduction trend continues until 2035 and applies to onshore wind as well, we forecast the capex to be $1517 per kW for onshore wind and $2341 per kW for offshore wind. O&M expenditures for land-based wind are expected to be $28 per kW annually in 2035 which amounts to 1.6% of capex (NREL, 2023a). O&M expenditrues for offshore wind are expected to be $105 per kW annually in 2035 which amounts to 4.5% of capex (NREL, 2023b). In the model, wind power is not able to export its power as it can produce electricity cheaper than market prices, making the optimisation unbounded.

Battery energy storage
BES is defined in the model as a storage technology that can store the power carrier. BES is present in both the EP and the GS configuration but serves slightly different purposes in both. In the EP configuration, batteries are primarily used to balance supply and demand, whereas in the GS, batteries can also be utilized to generate profit through trading on the power market. Similar to PV and wind power, BES systems use DC, which needs to be converted to AC when connected to the power grid. The round-trip efficiency of battery storage is reduced by inverter inefficiencies and heat generated by the batteries during charging, resulting in a round-trip efficiency of 85% (Cole & Karmakar, 2023). The storage loss is assumed to be zero, and the battery lifetime is expected to be 15 years (Cole & Karmakar, 2023).

Since the battery is a profit-generating asset, in cases of highly volatile day-ahead prices, its profitability could potentially exceed the interest rate of 9%. In such scenarios, the optimization could become unbounded, as increasing the battery capacity would result in perpetually higher profitability. To prevent this, the maximum storage capacity and energy capacity is constrained to the peak demand of 350 MWh and 350 MW respectively. However, because the model operates on hourly time steps, the energy output is inherently limited by the storage capacity, ensuring that no more energy can be discharged than the battery's total capacity. E.g., a BES system with a storage capacity of one MW will have an energy capacity of no more than one MW. The model optimizes both capacities, necessitating a cost for each. According to an NREL report, the expected 2035 capex are €206 per kWh and €280 per kW. (Cole & Karmakar, 2023). The reported O&M expenditures for BES systems vary widely, ranging from 1% to 10% of CAPEX annually. In the model we will use the median value of 3.96% (Cole & Karmakar, 2023).

Heat pump

Heat pumps are an important technology present in both system configurations. They are a conversion technology that can convert the power carrier into the heat carrier in the model. The performance of heat pumps is generally described by its COP. According to Eneco, their grid-scale air source heat pumps have an average COP of 3 throughout the year (Eneco, 2024b). Therefore, they can convert each kWh of power into 3 kWh of heat. The maximum capacity is not constrained in the model. Air to water heat pumps, such as the ones used in EPU's DHN, typically have a lifespan of 16 years (Toleikyte et al., 2023). According to EPU, these heat pumps cost €1600 per kW with O&M expenditures of 3% of CAPEX (Eneco, 2024d).

E-boiler

Similar to heat pumps, E-boilers are present in both system configurations and are a conversion technology that converts the power carrier into the heat carrier. E-boilers are less efficient compared to heat pumps with a 97% (Manni et al., 2022). These assets have a lifespan of 20 years and relatively low CAPEX of €400 per kW, with O&M expenditures amounting to 3% of CAPEX annually (Eneco, 2024c, 2024d).

Tank thermal energy storage

The TTES system is defined as a storage technology that stores the heat carrier. Eneco has recently built 15,826 m^3 of TTES volume across four separate storage vessels. Together, they can store 610 MWh of thermal energy and can deliver 100 MW to the DHN (Janse de Jonge et al., 2022). According to EPU, the capex for these storage assets is €35,6 per kWh with a lifetime of 20 years (Janse de Jonge et al., 2022). No cost for the energy capacity is defined. Therefore, the ratio of energy capacity to storage capacity is limited to a maximum of 0.164 (100/610). Due to the limited operation time of these tanks, EPU does not have available data on the thermal loss. However, according to nPro, TTES systems larger than 3000 m^2 lose on average 15% in 30 days which equates to an exponential decay of 0,023% per hour (nPro, n.d.). Similarly to the thermal loss, there is no empirical data on the maintenance expenditures. However, the expected maintenance cost over the system's lifetime is two million, which is roughly 0.5% of CAPEX annually (Janse de Jonge et al., 2022).

Aquifer thermal energy storage

Recent research by Eneco has identified that the ground beneath Utrecht is particularly well suited for ATES systems, which are modeled as a storage technology using heat as its energy carrier. The study evaluated multiple ATES configurations with capacities up to 1.9 million m^3 and 50 MW of which 2 could be located at EPU. It concluded that at location LW, the levelised cost of heat is lowest for a system with a storage capacity of 1.9 million m^3 and an output capacity of 35 MW (Remmelts, 2019). The evaluated high-temperature ATES stores water at 85°C, equating to 85.4 kWh per cubic meter. Therefore, the maximum storage capacity per ATES system is 162.26 thousand MWh, resulting in a combined capacity of 325 MWh with a total energy output of 100 MW.

Due to the temperature difference between the storage (85°C) and the DHN (120°C), a heat pump is used to extract thermal energy from the ATES system, which costs €210 per kW. The storage itself costs €0.15 per kWh, and operating expenses amount to 8.8% of capital expenditures annually (Remmelts, 2019). Although these OPEX might seem high compared to other assets, it is important to note that this also includes the cost of power to operate the extraction heat pump.

The expected lifetime of the heat pump is 16 years, while the storage system has an expected lifetime of 30 years. In the optimization model, a weighted average lifetime of 24.5 years (based on CAPEX costs) is used (Remmelts, 2019; Toleikyte et al., 2023).

Recent studies show that ATES systems can store energy for up to four months with a thermal recovery efficiency of 68% (Sommer et al., 2014). Remmelts' findings align with this, indicating efficiencies between 67% and 80%, depending on the location and system design (Remmelts, 2019). For the optimization model, a 70% efficiency over four months is assumed, corresponding to an exponential decay rate of 0.012% per hour.

It is important to acknowledge the inherent limitations of modelling an ATES system in this manner. In the model, the output heat pump is not represented as a separate asset. Instead, the electricity costs associated with the heat pump are included in the operational and maintenance expenditures. This approach reduces accuracy in two significant ways: the model does not account for the power demand required when thermal energy is extracted from the ATES, which would occur during real-world operations, and it assumes a constant average power price rather than incorporating variable power prices, which better reflect actual market dynamics. Despite these limitations, the simplification offers notable advantages. Modelling the extraction heat pump as a separate asset would require an additional energy carrier (ATES-Heat) and introduce more complexity to the model. This increased complexity would significantly affect solution time, particularly due to the additional energy carrier. As such, this simplification aims to strike a balance between real-world accuracy and model efficiency.

Peak boiler

Peak boilers are essential for providing supplemental thermal energy during peak hours when standard assets may not produce enough to meet demand. Additionally, they offer a cost-effective solution for creating redundancy, which is invaluable during maintenance on other assets. These conversion technologies operate by converting the fuel carrier into heat with an efficiency of 90% (Lara, 2022). They have a capital cost of 200 per kW, a lifespan of 30 years, and annual operational expenditures amounting to 3% of CAPEX (Eneco, 2024d).

Combined cycle gas turbines

Combined Cycle Gas Turbines (CCGTs) are another conversion technology capable of converting fuel into both heat and power. This dual functionality allows CCGTs to generate profit on the power markets by exporting electricity when prices are high. The resulting thermal energy can either be directly supplied to the DHN or stored for later use. By 2035, CCGTs are expected to achieve a power generation efficiency of 51% and produce 0.77 kWh of thermal energy per kWh of power (BNEF, 2023; Eneco, 2024a). LW07 is planned to have a maximum power capacity of 177 MW and will be capable of delivering 136 MW of thermal energy. Capital expenditures are €1,000 per kW, with operational expenditures amounting to 3% of CAPEX annually, and a lifetime of 30 years (Eneco, 2024d).

Solid state thermal energy storage

The final storage technology in the model is SSTES, which stores the high-heat carrier. The storage unit costs 85 per kWh and has a lifetime of 30 years. Thermal loss is 1% per day, corresponding to an exponential decay of 0.042% per hour. Eneco's SSTES systems are designed for 13-hour storage, meaning each kWh of storage provides 0.077 kW of energy capacity.

The charge/discharge cycle is modeled through two technologies: SSTES-charge and SSTES-discharge. The SSTES-charge technology is a power-to-heat conversion system, operating at 95% efficiency. Its CAPEX is 2,099.50 per kW, with a 15-year lifetime and annual OPEX of 3% of CAPEX. The SSTES-discharge technology converts the high-heat carrier back into heat to supply to the DHN. While it shares the same 15-year lifetime as the charge technology, it incurs no additional costs. This is because the charge and discharge functions are part of the same asset, and costs are only allocated to the charge technology to avoid double counting.

4

Fuel and power supply

The fuel- and power supply are represented as supply technologies importing the fuel and power carriers, respectively. These technologies introduce energy into the system at a predefined cost. The power supply operates based on power price curves, dictating the cost of electricity entering the system. Similarly, the hydrogen supply follows fuel price curves, determining the cost of fuel provided to the system. Both are already present at EPU and therefore do not require investment. However, both have yearly associated costs. The power connection incurs a monthly cost of €4 per kW, which equates to €48 per kW per year. Additionally, there is a variable cost of €0.0148 per kWh (Stedin, 2023). For the fuel supply, there is a yearly transport cost of €27.91 per m^3/h of capacity. Additionally, there is a periodic charge of €1.09 per m^3/h of capacity annually. Combined, this equates to €2.97 per kW per annum (Stedin, 2024).

Heat transmission

The heat transmission technology is defined as a transmission technology that facilitates the one-way transport of heat between locations. It transfers the heat carrier across the system, ensuring that heat is distributed efficiently from supply points to demand points without a return flow. Each transmission line has a predefined capacity (Figure E.2). As these lines are already in place, there are no investment costs associated with them.

4.6. ANALYSIS OF MODEL OUTPUT

As outlined in Chapter 4.5.1, there are three scenarios for power prices and four scenarios for fuel prices, resulting in a total of 12 scenarios when each power price scenario is combined with each fuel price scenario. Additionally, these scenarios are modelled across two system configurations, bringing the total to 24 model runs. The GridSync configuration is used to determine the capacities of P2H and F2H technologies, and these capacity outcomes are then applied in the EcoPure configuration to calculate the required RES capacity.

4.6.1. SYNTHETIC DATA

After optimising for the different capacities, it is crucial to assess the system's reliability under varying demand profiles, as ensuring that thermal demand is consistently met is a key priority for EPU. To evaluate reliability, Zheng et al. (2018) utilized Monte Carlo simulations to account for uncertainties in weather conditions. In the optimization model presented in this study, fluctuations in thermal demand can significantly affect system performance. Therefore, synthetic datasets will be generated from observed data using Monte Carlo simulation techniques to capture these variations.

The process begins by focusing on a single month. First, a daily demand profile is established for that month, calculated as the average hourly demand across all days. This results in a representative demand profile that reflects typical daily energy use for that specific month. Next, a probability distribution is developed to capture variations in the total daily demand for the month. This is done using Gaussian kernel density estimation (KDE), which is applied to the observed total daily demand values, creating a KDE that represents the likely range of daily demand totals. To simulate synthetic days, random draws are taken from the KDE, one for each day of the month. Each simulated daily demand value is then distributed according to the representative daily demand profile, resulting in a set of synthetic demand values that vary day-to-day but follow the typical hourly pattern. This process is repeated for each month of the year, resulting in 12 different KDEs and corresponding synthetic demand profiles. The outcome is a dataset that captures potential variations in thermal demand throughout the entire year, allowing for a robust evaluation of system reliability under a wide range of conditions.

However, this approach does not account for the serial correlation typically observed in thermal demand profiles, which are largely influenced by external temperatures. To address this, we calculated transition probabilities based on observed data to reflect the likelihood of consecutive high or low demand days. Specifically, for each day where demand exceeds the mean of its corresponding KDE, we determined the probability that the following day would also have above-average demand. Similarly, for days with demand below the mean, we calculated the probability that the next day would also have below-average demand. The results indicate that the probability of a high-demand day being followed by another high-demand day is 80%, while the probability of a low-demand day being followed by another low-demand day is 86%. Both probabilities are statistically significantly different from 0.5 ($p < 0.01$), which would be expected in the absence of serial correlation. Therefore, the random draws from the KDE have been adjusted to account for these probabilities. That is, if the preceding day had above-average demand, there is an 80% chance that the next random draw is taken from the right side of the KDE, ensuring that it simulates a higher demand. This adjustment simulates the serial correlation observed in the data, maintaining the natural tendency for consecutive high or low demand days. The operational performance of each of the optimisation results is then evaluated against a synthetic dataset spanning 2 years of data.

4.6.2. MODEL SIMPLIFICATION

From the literature review we can identify that most optimisation studies in energy systems make use of representative days to manage computational complexity. The most adopted approach in energy systems is K-means clustering due to its computational efficiency for large datasets with multiple dimensions. However, the use of representative days does inherently reduce the accuracy of the data and therefore reduces the accuracy of results. To evaluate the performance loss from a model that implements representative days, we will run the $GT_{removal}$ model both over the full and a clustered dataset. To determine the optimal number of clusters, we employ the widely used elbow method. This approach involves executing the k-means algorithm for various values of k (referring to the number of clusters) and evaluating the resulting within-cluster sum of squares (WCSS). By plotting the WCSS against the corresponding values of k , an "elbow point" can be visually identified, indicating where the reduction in WCSS diminishes as additional clusters are added.

While not as prevalent in the reviewed scientific literature, Calliope offers an alternative approach to reduce solution time through masked time resolution adjustment. This method involves resampling data into larger time steps in selected areas while maintaining full resolution in unmasked, critical areas. Unmasking is achieved by evaluating input data, such as thermal demand, and selecting a preset number of high-demand days to retain at full resolution. To assess this simplification technique, the model will be configured to keep the 15 highest-demand days at full hourly resolution, while the remaining data is resampled into 6-hour time steps. This adjustment reduces the number of data points from 8,760 to 1,760, significantly enhancing computational efficiency.

5

Results & Discussion

This chapter presents the results of the optimisation process for the two system configurations: GridSync and EcoPure. In total, 12 scenarios were considered for each configuration, combining three power price scenarios with four fuel price scenarios. Through the analysis, it became apparent that the optimisation results are most consistent across the different power price scenarios within each fuel price scenario. As a result, the optimisation outcomes will be discussed primarily by fuel scenario, with comparisons made across both configurations where relevant.

The objective of this chapter is to address sub-research question 5:

- Which level of resilience can be achieved and what is comparative resilience of a system designed for multi-year reliability compared to those optimised for typical day scenarios?

5.1. GridSync system configuration

The results indicate that the voluntary and bifurcation scenarios produce very similar outcomes, relying primarily on fuel as the main energy source. In contrast, the removal scenario shows a hybrid approach, utilizing both fuel and power-to-heat (P2H) technologies. The hydrogen scenario, on the other hand, results in an almost all-electric system, relying predominantly on P2H and using fuel only to meet peak demand. Therefore, the results for the voluntary and bifurcation scenarios will be presented together, while the removal and hydrogen results will be presented separately. Furthermore, battery and solid-state thermal energy storage capacities are optimized to zero across all scenarios, as they are outcompeted by the more cost-effective ATES and TTES solutions. Consequently, these technologies will not be discussed further.

5.1.1. Scenario: Voluntary & Bifurcation

In the voluntary and bifurcation scenario, CO_2-compensated natural gas prices average €0.047 and 0.051 per kWh over the year, making it more competitive than the average power prices of €0.085, €0.081, and €0.054 for the LI, GT, and SP scenario, respectively. As a result, the optimisation outcomes indicate that EPU should primarily rely on natural gas as its energy source in the voluntary and bifurcation scenarios. Specifically, in the LI and GT scenarios, the optimisation results show a complete reliance on natural gas, with no capacity allocated to power-to-heat (P2H) systems. Conversely, in the SP scenario, power prices are not only lower but also more volatile due to the higher penetration of renewable energy sources. This volatility creates strategic opportunities throughout the year, allowing EPU to take advantage of exceptionally low power prices. As a result, in the SP scenario, the optimisation suggests a combination of P2H and natural gas as the most effective energy strategy. However, P2H remains a small fraction of the overall operational thermal energy supply, with fuel still playing a significant role.

Storage

Across all three power scenarios, the optimised capacity for aquifer thermal energy storage (ATES) shows consistent results, ranging from 86 MW to 90 MW, with storage capacity varying from 38.6 GWh to 64.4 GWh. In contrast, tank thermal energy storage (TTES) shows much lower and less consistent optimised energy and storage capacities, ranging from 5.6 MW to 50.2 MW and 34 MWh to 306 MWh, respectively.

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Technology	LI_{vol}	GT_{vol}	SP_{vol}	LI_{bif}	GT_{bif}	SP_{bif}
$ATES_{capacity}$	90.0	87.3	86.0	89.6	87.1	85.9
$ATES_{storage}$	47,056.8	44,323.4	51,844.9	46,086.4	38,604.8	64,440.6
$TTES_{capacity}$	50.2	43.0	5.6	50.1	41.8	9.7
$TTES_{storage}$	305.9	262.2	34.0	305.6	255.0	59.2

Table 5.1: The optimised energy (MW) and storage (MWh) capacity for each storage technology across three different power scenarios for the voluntary (vol) and bifurcation (bif) fuel scenario.

Power technology

As previously mentioned, the SP scenario is the only one that integrates power-to-heat technology, with 11 MW provided by heat pumps and 63 MW by E-boilers in the voluntary scenario, and 28 MW provided by heat pumps and 59 MW by E-boilers in the bifurcation scenario.

Technology	SP_{vol}	SP_{bif}
Heat pump	10.9	28.1
E-boiler	63.0	58.7
Grid supply	68.6	69.9

Table 5.2: P2H results vol & bif scenario

The optimised energy capacity in MW for each power technology across three different power scenarios

Fuel technology

Across all scenarios, the CCGT is optimised to the maximum of 177 MW_e providing an additional 136 MW_{th}. Furthermore, across all power scenarios peak boilers are included ranging from 65 to 113 MW to satisfy peaks in thermal demand.

Technology	LI_{vol}	GT_{vol}	SP_{vol}	LI_{bif}	GT_{bif}	SP_{bif}
CCGT	177_e	177_e	177_e	177_e	177_e	177_e
Peak boiler	99.7	110.9	82.9	100.3	112.5	65.2
Fuel supply	457.9	470.3	439.2	458.5	472.0	419.5

Table 5.3: The optimised energy capacity in MW for each fuel technology across the three different power scenarios

Economic performance

When evaluating the economic performance of the system, three key indicators are considered: levelised cost of heat (LCOH), capital expenditures (CAPEX), and the objective value. The first indicator, levelised cost of heat, represents the average cost per kWh of heat produced, accounting for all system costs and revenues over the system's lifetime. From the results, it becomes clear that as power prices decrease, the LCOH increases. The voluntary results show a LCOH of €0.01, €0.016, and €0.034 for the LI, GT, and SP scenario, respectively. The bifurcation results show a LCOH of €0.019, €0.024, and €0.038 for the LI, GT, and SP scenario, respectively.

Regarding CAPEX, the optimisation results for the LI and GT scenarios are very similar, showing almost identical results. However, the SP scenario is significantly more expensive due to the inclusion of high-cost assets such as HPs and E-boilers. It is important to note that CAPEX only reflects the upfront investment costs and does not account for operational expenditures (OPEX). The results show CAPEX ranging from €25.2 to €35.6 million .

The objective value, in contrast, incorporates both CAPEX and OPEX. The results indicate that in some scenarios, the objective value is lower than the CAPEX, meaning the net present value of operational cash flows over the system's lifetime is negative. Concluding that the revenues from power sales exceed operational costs in those scenarios. In the other scenarios, the objective value is higher than the CAPEX, signifying that the net present value of operational cash flows is positive. Concluding that operational expenditures exceed revenues from power sales. The results show the objective value ranging from €11.2 to €41.6 million.

Cost	LI_{vol}	GT_{vol}	SP_{vol}	LI_{bif}	GT_{bif}	SP_{bif}
LCOH	0.010	0.016	0.034	0.019	0.024	0.038
CAPEX	25.32	25.30	32.44	25.30	25.21	35.60
Objective	11.16	17.58	36.33	20.01	26.16	41.60

Table 5.4: The levelised cost of heat (in EUR), and CAPEX and objective value (in million EUR).

Operational performance

As mentioned previously, the voluntary and bifurcation scenarios mostly rely on fuel as its main energy source with the CCGT providing between 45% and 79% of all thermal thermal supply. The peak boiler, provides between 11% and 26% of all thermal supply. In the SP scenario, P2H is included with heat pumps providing between 8% and 20% of supply and E-boilers between 24% and 28%.

Across the two fuel scenarios peak thermal capacity ranges from 376.2 MW to 423.1 MW. However, the capacity from storage assets is not certain as the state of charge might constrain capacity during certain periods. Therefore, a more reliable indicator of peak thermal capacity is the flex-capacity, which excludes storage assets, showing what thermal capacity is always dispatchable. Flex-capacity ranges from 236 MW to 327.5 MW. Peak thermal demand for the simulated data is 390.4 MW. Therefore, only the SP scenarios have enough thermal capacity to cover demand. However, none of the scenarios have enough flex-capacity to fulfil simulated thermal demand with the maximum unmet demand ranging from 38.9 MWh to 88.1 MWh. Consequently, the loss of power supply probability (LPSP) ranges from 0.023% to 0.063%.

KPI	LI_{vol}	GT_{vol}	SP_{vol}	LI_{bif}	GT_{bif}	SP_{bif}
Heat pump (%)	0	0	8	0	0	20
E-boiler (%)	0	0	28	0	0	24
CCGT (%)	79	75	47	79	74	45
Peak boiler (%)	21	25	18	21	26	11
Thermal capacity (MW)	376.2	377.5	384.7	376.3	377.7	383.9
Flex-capacity (MW)	236.0	247.2	293.1	236.6	248.7	288.3
LPSP (%)	0.063	0.054	0.023	0.063	0.053	0.024

Table 5.5: The operational KPIs across the different scenarios.

5.1.2. Scenario: Removal & Hydrogen

In the removal scenario, CO_2-compensated natural gas prices average €0.068 per kWh over the year, making it more competitive than the average power prices of €0.085 and €0.081 for the LI and GT scenarios, respectively, but less competitive than the average power price of €0.054 in the SP scenario. However, the higher volatility in power markets creates strategic opportunities throughout the year, enabling EPU to capitalize on low power prices through power-to-heat technology. As a result, the removal scenario follows a hybrid approach, relying on both fuel and power technologies as the most effective energy strategy. Conversely, the hydrogen scenario demonstrates an almost complete reliance on power-to-heat technologies, as the forecasted average blue hydrogen price of €0.115 is not competitive with any of the power scenarios.

Storage

Across all three power scenarios, the optimised capacity for aquifer thermal energy storage remains consistent at 100 MW, with storage capacity ranging from 63.5 GWh to 132.2

GWh in the removal scenario, and from 105.0 GWh to 172.0 GWh in the hydrogen scenario. In contrast, the optimised capacity for tank thermal energy storage is significantly lower, ranging from 42.4 MW to 52.4 MW, with storage capacity varying from 258.8 MWh to 319.3 MWh across both fuel scenarios.

Technology	LI_{rem}	GT_{rem}	SP_{rem}	LI_{hyd}	GT_{hyd}	SP_{hyd}
$ATES_{capacity}$	100	100	100	100	100	100
$ATES_{storage}$	63,633.4	63,506.1	132,240.8	110,169.0	104,989.2	171,988.4
$TTES_{capacity}$	50.1	42.4	52.2	52.2	52.4	52.2
$TTES_{storage}$	305.5	258.8	318.4	318.5	319.3	318.4

Table 5.6: The optimised energy capacity (MW) and storage capacity (MWh) for each storage technology across three different power scenarios

Power technology

As previously mentioned, all power scenarios in both the removal and hydrogen fuel scenarios incorporate power-to-heat technologies. In the removal scenario, the optimised heat pump capacity ranges from 49.9 MW to 131.9 MW, whereas in the hydrogen scenario, the heat pump capacity ranges from 151.7 MW to 161.7 MW. E-boilers are not included in any of the scenarios.

Technology	LI_{rem}	GT_{rem}	SP_{rem}	LI_{hyd}	GT_{hyd}	SP_{hyd}
Heat pump	49.9	66.5	131.9	160.2	161.7	151.7
E-boiler	0	0	0	0	0	0
Grid supply	16.6	22.2	44.0	53.4	53.9	50.6

Table 5.7: The optimised energy capacity in MW for each power technology across three different power scenarios

Fuel technology

The optimised capacity of the CCGT is where the removal scenario and the hydrogen scenario start to deviate. In the removal scenario, EPU partially relies on CCGT technology, with capacities ranging from 49.0 MW to 177 MW_e, whereas in the hydrogen scenario, this technology is not included. Conversely, both fuel scenarios still rely on peak boilers to satisfy peaks in thermal demand. The optimised capacity for peak boilers ranges from 32.3 MW to 71.8 MW.

Economic performance

For the removal scenario, LCOH shows very similar results across the power scenarios ranging from €0.054 to €0.056. For the hydrogen scenario, LCOH is more variable across the power scenarios ranging from €0.056 to €0.068.

Across both fuel scenarios, CAPEX shows very similar results ranging from €35.2 million €41.7 million. The objective value, in contrast, incorporates both CAPEX and OPEX and ranges from €58.1 million to €75.9 million.

Technology	LI_{rem}	GT_{rem}	SP_{rem}	LI_{hyd}	GT_{hyd}	SP_{hyd}
CCGT	177_e	177_e	49.0_e	0	0	0
Peak boiler	40.0	32.3	53.9	63.3	61.8	71.8
Fuel supply	391.5	383.0	155.9	70.4	68.7	79.7

Table 5.8: The optimised energy capacity in MW for each fuel technology across the three different power scenarios

Cost	LI_{rem}	GT_{rem}	SP_{rem}	LI_{hyd}	GT_{hyd}	SP_{hyd}
LCOH	0.054	0.056	0.055	0.068	0.067	0.056
CAPEX	35.2	38.4	40.7	41.5	41.7	40.9
Objective	58.1	60.8	61.9	75.9	74.3	64.1

Table 5.9: The levelised cost of heat (in EUR), and CAPEX and objective value (in million EUR).

Operational performance

Operationally, the results show a clear distinction between the removal and hydrogen scenario. In the removal scenario, fuel remains the main energy source, with CCGT technology providing 66% of the thermal energy supply in the LI scenario and 57% in the GT scenario. In the SP scenario, however, P2H becomes more important with 89% of thermal supply coming from heat pumps. Conversely, in the hydrogen scenario, P2H is the most important energy source across all power scenarios with 99% of thermal supply coming from heat pumps.

The total thermal peak capacity across both fuel scenarios is very similar ranging form 375.7 MW to 377.6 MW and flex-capacity ranging from 223.5 MW to 235.2 MW. In all scenarios, the LPSP is higher than zero, ranging from 0.056 to 0.067, due to peak capacity being lower than peak demand in the synthetic data.

KPI	LI_{rem}	GT_{rem}	SP_{rem}	LI_{hyd}	GT_{hyd}	SP_{hyd}
Heat pump (%)	31	42	89	99	99	99
E-boiler (%)	0	0	0	0	0	0
CCGT (%)	66	57	10	0	0	0
Peak boiler (%)	3	2	1	1	1	1
Thermal capacity (MW)	376.3	377.6	375.7	375.7	375.8	375.7
Flex-capacity (MW)	226.2	235.2	223.5	223.5	223.5	223.5
LPSP (%)	0.063	0.056	0.067	0.067	0.067	0.067

Table 5.10: The operational KPIs across the different scenarios.

5.1.3. DISCUSSION

From the results, it becomes clear that the power and fuel prices together influence the asset mix for EPU. Generally, we observe that as power prices decrease relative to fuel prices, the system increasingly relies on power-to-heat technologies. Conversely, when power prices rise relative to fuel prices, the system shifts toward fuel-based technologies. This relationship can be quantified by examining the power-to-fuel price ratio.

Power technology

To understand how the power-to-fuel price ratio affects the installed capacity we made use of regression analysis. The regression analysis reveals a statistically significant negative relationship between power/fuel inputs and the adoption of power-to-heat (P2H) technologies (Appendix C.1). That is, as power/fuel levels increase, the implementation of P2H technologies decreases. This relationship is robust, as indicated by an R^2 value of 0.95, suggesting that 95% of the variation in P2H adoption is explained by changes in power/fuel inputs. Additionally, the model's F-test p-value is less than 0.01, confirming the statistical significance of the regression model and the strong explanatory power of the independent variable. Within P2H technology, heat pump (HP) capacity scales linearly with total P2H capacity ($R^2 = 0.93$ with $p < 0.01$) while E-boiler capacity does not (Appendix C.2). The division of P2H capacity across HPs and E-boilers can be explained by their characteristics. Heat pumps are more expensive than E-boilers, with CAPEX of 1600 per kW compared to 400 per kW for E-boilers. However, HPs are also more efficient, realising a coefficient of performance of 3 compared to 0.97 for E-boilers. These characteristics make HPs better suited for continuous operation, whereas E-boilers are more suitable for intermittent use to meet peaks in demand. E-boiler capacity is only larger than 0 between a power-to-fuel ratio of 0.794 and 1.191. This can be explained by the fact that between these ratios, power is intermittently cheap enough to use it as a peak source, but not yet cheap enough to use it as a baseload source. However, once power does become cheap enough relative to fuel prices, inclusion of E-boilers is no longer required as the more efficient HPs can take over continuous operation.

Fuel technology

Conversely, the regression analysis indicates a statistically significant positive relationship between power/fuel inputs and the adoption of fuel-to-heat (F2H) technologies (Appendix C.3). That is, as power/fuel levels increase, the implementation of F2H technologies also increases. The model demonstrates a strong explanatory power, with an R^2 value of 0.84, indicating that 84% of the variance in F2H adoption is accounted for by power/fuel levels. The F-test p-value is less than 0.01, confirming the statistical significance of the regression model and the strong explanatory power of the independent variable. Between a power-to-fuel ratio of 0.739 and 1.059, the installed CCGT capacity increases linearly from 0 to the maximum of 177 MW_e. The peak boiler capacity exhibits a second-degree polynomial relationship with the power-to-fuel ratio with an R^2 value of 0.64 and $p < 0.05$ (Appendix C.4). This regression indicates an overall positive correlation with the power-to-fuel ratio, though capacity slightly decreases in the range where the CCGT scales up.

Storage

Both the P2H and F2H technologies increase flex-capacity in the system, which can be used to explain the storage capacity of tank thermal energy storage (Appendix C.5). The regression analysis with TTES storage capacity as its dependent variable and flex-capacity as the independent variable indicates a statistically significant negative relationship. The model demonstrates a strong explanatory power, with an R^2 value of 0.96 and an F-test p-value of less than 0.01, confirming the statistical significance of the regression model. These results can be attributed to the characteristics of TTES, which make it most suitable for balancing short-term supply and demand. Consequently, as flex-capacity increases, the system relies less on TTES for short-term peak supply. The short-term nature of TTES is evident in the model's behaviour, which shows high volatility in its state of charge (Appendix C.10). Furthermore, the results show that ATES capacity is optimised close to the maximum energy capacity of 100 MW across all 12 scenarios with storage capacity showing more variation ranging from 38.6 GWh to 172.0 GWh. These large energy and storage capacities can be attributed to two key factors. First, ATES is highly cost-effective compared to other forms of thermal energy storage, with a cost of 0.15 per kWh. Second, ATES demonstrates remarkable efficiency for long-term storage, with only a 30% thermal loss over a four-month storage period. These characteristics make ATES ideal for seasonal thermal energy storage, justifying the need for large storage capacity. The seasonal nature of ATES is evident in the model's behaviour, with its state of charge increasing during low-demand periods and decreasing during high-demand periods (Appendix C.11). The total ATES storage capacity, can best be explained by the operational fraction of HPs (Appendix C.6). Given that renewable feed-in is typically higher during the summer months, power prices tend to be lowest at that time. During these periods of low power prices, HPs can be used to generate inexpensive thermal energy, even when there is no immediate demand. This thermal energy can instead be stored in seasonal aquifer thermal energy storage, thus requiring a larger storage capacity. The regression model demonstrates a strong explanatory power, with an R^2 value of 0.83 and an F-test p-value of less than 0.01, confirming the statistical significance of the model.

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Economic performance

The results of economic performance show that in some scenarios the objective value is lower than capital expenditures. This only occurs in scenarios where the power-to-fuel ratio is above 1.588, signifying that fuel is much cheaper than power. In these scenarios, the CCGT generates sufficient revenue from power sales to offset all other operational expenditures, resulting in a net negative operational cost. Furthermore, we can explain the levelised cost of heat (LCOH) with the power-to-fuel ratio (Appendix C.7). The regression shows a statistically significant negative relationship with an $R^2 = 0.79$ and a p-value smaller than 0.01. Similarly to the results observed in the objective value, this result can be explained by the revenue from CCGT operation. As the power-to-fuel ratio decreases, CCGT capacity declines, reducing the ability to offset operational expenditures with revenue from power sales and consequently increasing the LCOH.

Operational performance

The primary indicator of operational performance is the loss of heat supply probability (LHSP). Since EPU is solely responsible for providing thermal energy to households connected to the district heating network, their main objective is to achieve an LHSP of 0. However, across all operational model runs, the LHSP is greater than 0 due to peak demand in the synthetic data exceeding peak demand in the observed 2023 data used for optimisation. The LHSP can be explained by two factors: the total thermal capacity and flex-capacity as a percentage of peak demand (Appendix C.8 & C.9). The multiple regression model demonstrates strong explanatory power, with an R^2 value of 0.99 and p-values for both coefficients below 0.05.

5.2. ECOPURE SYSTEM CONFIGURATION

In the EcoPure system configuration, power comes directly from three renewable sources (RES): photovoltaic, and offshore and onshore wind. To optimise the capacity of these renewable energy sources, the results from the GridSync system configuration are used as a starting point to answer how much renewable power capacity would be required to fully rely on direct renewable power. In all scenarios where P2H is optimised to be 0, the renewable power sources are also 0 and will therefore not be discussed. Therefore, within the voluntary and bifurcation scenarios, only the SP power scenario will be discussed. Conversely, all power scenarios will be discussed for the removal and hydrogen scenario.

5

Renewable energy sources

From the results, we can observe that the installed capacity of RES is most consistent across power scenarios with exception of the hydrogen fuel scenario. Across the voluntary, bifurcation, and removal scenarios, the optimised peak capacity of PV ranges from 62.6 to 76.90 MW and onshore wind ranges from 21.79 to 47.82 MW for the SP power scenario. In the removal fuel scenario, all power scenarios include P2H and therefore rely on RES. Within this scenario, PV capacity ranges from 23.3 to 30.96 MW and onshore wind ranges from 21.79 to 28.68 for the LI and GT power scenario. None of these scenarios include offshore wind.

Conversely, the hydrogen scenario does include offshore wind and shows very different results. Across the hydrogen scenario, the optimised PV capacity is much lower, ranging from 5.53 to 9.88 MW while offhore wind shows comparatively high results ranging from 8,159.92 to 9,052.08 MW.

RES	SP_{vol}	SP_{bif}	LI_{rem}	GT_{rem}	SP_{rem}	LI_{hyd}	GT_{hyd}	SP_{hyd}
Photovoltaic	90.68	87.8	23.22	30.96	62.07	9.88	8.99	5.53
Onshore wind	6.58	18.62	21.99	28.68	56.89	0	0	0
Offshore wind	0	0	0	0	0	8,989.08	9,052.08	8,159.92

Table 5.11: Peak capacity for the renewable energy sources across the different scenarios in MW

Economic performance

The results indicate that the LCOH increases across each subsequent scenario, demonstrating a positive correlation with fuel prices and a negative correlation with power prices—except in the hydrogen scenario. In the voluntary, bifurcation, and removal scenarios, the LCOH ranges from 0.036 to 0.059. However, in the hydrogen scenario, the LCOH shows a significant rise, with values ranging from 1.65 to 1.91.

Both CAPEX and the objective value follow a similar pattern, remaining relatively stable across the voluntary, bifurcation, and removal scenarios, but showing a substantial increase in the hydrogen scenario. In these first three scenarios, CAPEX ranges from 33.89 to 49.70 million euros, rising sharply to range 1903.40 to 2107.85 million euros in the hydrogen scenario. Similarly, the objective value ranges from 38.67 to 65.18 million euros in the initial scenarios and increases to 1904.40 to 2108.98 million euros in the hydrogen scenario.

RES	SP_{vol}	SP_{bif}	LI_{rem}	GT_{rem}	SP_{rem}	LI_{hyd}	GT_{hyd}	SP_{hyd}
LCOH	0.036	0.041	0.052	0.054	0.059	1.9	1.91	1.65
CAPEX	33.89	38.64	38.63	42.90	49.70	2093.31	2107.85	1903.20
Objective	38.67	43.51	56.10	58.4	65.18	2094.49	2108.98	1904.40

Table 5.12: The levelised cost of heat (in EUR), and CAPEX and objective value (in million EUR)

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Operational performance

For the EcoPure system configuration, thermal peak capacity and flex capacity remain unchanged from the GridSync configuration, as the optimised capacity of thermal assets is replicated. Additionally, we assume that the Loss of Power Supply Probability (LPSP) remains consistent in the EcoPure configuration. If the installed wind and solar capacity is insufficient to power the P2H assets, EPU can still rely on its grid connection to meet demand. Thus, assuming EPU prioritises thermal supply over its goal of 100% renewable power, the LPSP would not fall below the levels observed in the GridSync configuration.

From the results we can observe that the output from P2H technologies as a percentage of total thermal supply, ranges from 23% to 43% across the voluntary, bifurcation, and removal scenarios, except for SP_{rem}, which exhibits an operational fraction of 85%. In the hydrogen scenario, P2H is almost entirely responsible for thermal supply with the operational fraction at 99% across all power scenarios.

KPI	SP_{vol}	SP_{bif}	LI_{rem}	GT_{rem}	SP_{rem}	LI_{hyd}	GT_{hyd}	SP_{hyd}
Heat pump (%)	8.64	21.79	32.51	43.27	85.36	99.16	99.19	99.18
CCGT (%)	49.35	47.84	63.44	54.47	14.13	0	0	0
E-boiler (%)	14	13.7	0	0	0	0	0	0
Peak boiler (%)	27.75	16.67	4.05	2.26	0.51	0.84	0.81	0.82

Table 5.13: The operational KPIs across the different scenarios.

5.2.1. DISCUSSION

From the results we can observe that the installed RES capacity tends to increases with the total $P2H_e$ capacity (Appendix C.12). However, we can also observe that this relationship follows different trajectories across fuel scenarios. In the voluntary, bifurcation, and removal scenario, RES capacity increases linearly with P2H to a max of 118.96 MW. The model demonstrates a strong explanatory power, with an R2 value of 0.93, indicating that 93% of the variance in RES capacity is accounted for by P2H capacity. The F-test p-value is less than 0.01, confirming the statistical significance of the regression model and the strong explanatory power of the independent variable. However, this model does not have strong explanatory power when applied to the hydrogen scenario which shows much higher RES capacity at similar P2H capacities. Therefore, another variable must be responsible for the discrepancy across fuel scenarios. Thermal supply from P2H as a percentage of total thermal supply seems to be responsible for the discrepancy. Although peak P2H capacity shows a similar range across all natural gas scenarios, P2H is responsible for a much higher percentage of total thermal supply in the hydrogen scenario. A regression model shows a positive correlation between the operational P2H fraction and installed RES capacity with an R^2 value of 0.72 and a p-value smaller than 0.01 (Appendix C.13). However, visually we can observe a break in the regression around an operational P2H fraction of 85% warranting the implementation of a chow test. The Chow test shows an F value 876.3 with a p-value < 0.01 indicating strong statistical evidence to reject the null hypothesis, which states that there is only one consistent regression model across the entire range of data. This implies that there is likely a structural break at an operational P2H fraction of 85%, beyond which the required RES capacity begins to increase much more rapidly (Appendix C.14 & C.15).

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This result is also reflected in the system's economic performance. Across all scenarios, the CAPEX and consequently the objective value is higher compared to the GridSync configuration. This is unsurprising, as additional investments are required not only for P2H, F2H, and storage assets but also to achieve the necessary RES capacity. When analysing the LCOH, we observe that in the voluntary, bifurcation, and removal scenarios, the results is only slightly higher compared to the GridSync scenario and even lower in the LI_{rem} and GT_{rem} scenarios. This indicates that, although upfront investment costs are higher, the long-term benefits of RES capacity remain financially viable. However, due to the rapidly increasing RES capacity requirements beyond an operational P2H fraction of 85%, systems with a higher fraction become financially unfeasible. This is reflected in the hydrogen scenario, where the LCOH ranges from 1.65 to 1.91.

When comparing the operational results from the EcoPure system configuration to those from the GridSync configuration, we observe that the output from P2H technologies, as a percentage of total thermal supply, remains largely unchanged. However, in the voluntary and bifurcation scenarios, the distribution of thermal supply across fuel technologies shifts, with a greater proportion coming from the peak boiler. This can be explained by the availability of inexpensive renewable power during periods when market prices would otherwise be high. As a result, the CCGT operates less frequently to supply power for the P2H assets, reducing its operational fraction. Conversely, the inflexibility of RES may require P2H to scale down during periods of low RES supply, with peak boilers stepping in to meet demand.

Finally, we observe that only the hydrogen scenario includes offshore wind, while all other scenarios rely on a mix of PV and onshore wind. Offshore wind is included in the hydrogen scenario, despite its higher cost, due to its typically higher average capacity factor—an increasingly important factor as a greater portion of operations relies on power.

5.3. MODEL SIMPLIFICATION

As mentioned in the Methodology, we will evaluate the comparative performance of two simplification methods; k-means clustering and masked time resolution adjustment. To evaluate the results, we will make use of the GT_{rem} scenario.

5.3.1. K-MEANS CLUSTERING

In the reviewed literature, the most used technique for model simplification is the use of representative days through k-means clustering. To re-run the GT_{rem} model with the use of representative days, we first evaluated the required number of clusters through the elbow-method. Visually, we can identify an elbow point at a k value of six. A Chow test, comparing the WCSS curve before and after the elbow point shows an F value 15.28 with a p-value < 0.01 indicating strong statistical evidence to reject the null hypothesis, which states that there is only one consistent regression model across the entire range of data. This implies that there is likely a structural break at a k value of 6.

Running the optimisation model with 6 representative days significantly improves solution time, reducing it from 273 seconds for a full-range optimisation to just 5 seconds, a 98.17% reduction. This result demonstrates that clustering is indeed an effective method for reducing solution time. However, the loss of high fidelity in input data for optimisation does impact performance. The difference in optimised capacities ranges from 0% to -21.44%, with an outlier at the peak boiler capacity, which shows a reduction of -100%. For storage capacity, differences range from -21.44% to 27.26%.

Technology	Full dataset	Clustering	Difference
$ATES_{cap}$	100,000	92,379	-7.62%
Heat pump	66,526	53,877	-19.01%
$TTES_{cap}$	42,448	33,348	-21.44%
CCGT	177,000	177,000	0%
Peak boiler	32,335	0	-100%
$ATES_{stor}$	63.506.054	80.820.903	27,26%
$TTES_{stor}$	258,829	203,342	-21.44%

Table 5.14: The optimized capacities for both the full optimization and the clustered optimization, along with their respective differences.

The largest discrepancy between full optimisation and the representative-day model appears in operational performance, with the LPSP increasing from 0.056% to 0.5%, an 792.86% increase.

KPI	Full dataset	Clustering	Difference
Thermal capacity	377,599	315,893	-16.34%
Flex capacity	235,151	190,167	-19.13%
LPSP (%)	0.056	0.500	792.86%

Table 5.15: Operational KPIs for the full and clustered optimisation, along with their respective differences

5.3.2. MASKED TIME RESOLUTION ADJUSTMENT

The second model simplification evaluated is masked time resolution adjustment. This approach results in a substantial reduction in solution time, decreasing from 273 seconds to 23 seconds, a reduction of 91.58%. The differences in optimized capacities compared to the full optimization are minimal, ranging from 0% to 1.8%, with a single outlier of -4.69% observed in peak boiler capacity. For storage capacities, the differences are similarly minor, with ATES showing a deviation of -1.47% and TTES showing a deviation of 0.63%.

Technology	Full dataset	Adjustment	Difference
$ATES_{cap}$	100,000	100.000	0%
Heat pump	66,526	67.721	1.8%
$TTES_{cap}$	42,448	42.716	0.63%
CCGT	177,000	177,000	0%
Peak boiler	32,335	30.820	-4.69%
$ATES_{stor}$	63.506.054	62.575.126	-1.47%
$TTES_{stor}$	258,829	260.465	0.63%

Table 5.16: The optimized capacities for both the full optimization and the masked time resolution adjustment optimization, along with their respective differences.

Due to the small variations in optimized capacities, the system's total thermal capacity deviates by only -0.01%, with flex capacity showing a -0.14% difference. Consequently, the Loss of Power Supply Probability closely matches the full optimization, with a value of 0.054, 3.57% lower than that observed in the full optimization.

KPI	Full dataset	Adjustment	Difference
Thermal capacity	377,599	377.548	-0.01%
Flex capacity	235,151	234.831	-0.14%
LPSP (%)	0.056	0.054	-3.57%

Table 5.17: Operational KPIs for the full and masked time resolution adjustment optimisation, along with their respective differences

5.3.3. DISCUSSION

As observed in the comparison, k-means clustering provides a rapid and effective approach, yielding satisfactory results. However, the clustered model particularly struggles to estimate the required capacity for the peak boiler accurately. When clustering demand days with k-means, the centroid of the high-demand cluster represents the average demand of those days, leading to an averaging effect that can smooth out peak values. Consequently, the centroid's demand is often lower than the actual peak demand observed on individual high-demand days. This smoothing effect reduces the apparent need for peak boilers to handle extreme values, resulting in a tendency for clustering to underestimate the required capacity for peak assets. This underestimation is reflected not only in the peak boiler capacity but also in the TTES capacity, as both are critical peak assets.

To address this shortcoming, one possible solution is to account for the real observed peak demand by adding sufficient peak capacity to meet these extreme demands to clustered results. While this approach would improve solution time, it's important to note that it would result in a higher objective value compared to a full optimization, achieving only a near-optimal solution. Applying this method for the observed maximum demand of 390 MW in the synthetic data, we can add the cheapest peak source until flex-capacity and thermal capacity reach a value where the expected LPSP equals 0.

However, the full optimization does not achieve a Loss of Power Supply Probability of 0. To enable a fair comparison between the adjusted approach and the full optimization, we will adjust the peak boiler capacity so that the thermal peak capacities in both the full and clustered optimizations are equal, resulting in a comparable LPSP of 0.056. To achieve this, an additional 61.7 MW would need to be added to the clustered optimization results, incurring an additional cost of 12.3 million euros. Consequently, the adjusted clustering approach has approximate capital expenditures of 49.6 million euros and an objective value of 66.8 million euros, which are 22% and 10% higher, respectively, than those of the full optimization.

Compared to k-means clustering, the masked time resolution adjustment method yields results that more closely align with the full optimization. This can be attributed to the inherent nature of energy system optimization, which often faces bottlenecks. When optimization is constrained to achieve an LPSP of 0, outcomes are largely dictated by high-demand periods, as supply must meet demand during these peak times. The masked time resolution adjustment approach takes advantage of this characteristic by maintaining full resolution in high-demand periods, where accurate modelling is critical, while reducing the resolution in lower-demand periods that have less impact on results. Therefore, this strategy achieves highly accurate results while still significantly reducing solution time. However, because masked time resolution adjustment retains a larger input dataset compared to k-means clustering, the solution time is longer. While k-means clustering provides a solution in 5 seconds, masked time resolution adjustment requires 23 seconds, showing a trade-off between solution time and accuracy.

6

From analysis to application: Results from a Multi-actor perspective

As outlined in Chapter 5, the optimisation results encompass a range of configurations, from entirely fuel-based systems to hybrid systems, and finally to (almost) fully electric systems. These outcomes stem from an optimisation model designed to prioritise the lowest cost, with each resulting system design having distinct implications for the multi-actor environment. Therefore, the objective of this chapter is to interpret the optimisation outcomes through a multi-actor perspective, examining how the broader decision-making environment influences each result.

6.1. Emission policy

In the voluntary and bifurcation scenarios, the optimisation model indicates an almost complete reliance on CO_2-compensated natural gas. Four out of six power scenarios exhibit a 100% operational fuel-to-heat fraction, while the remaining two scenarios demonstrate fractions of 65% and 56%, respectively. While these outcomes ensure the lowest lifecycle costs in their respective scenarios, relying so heavily on natural gas might prove politically complex. Both the national government and the municipality of Utrecht have set ambitious sustainability goals, aiming to be climate neutral in 2050 (Rijksoverheid, 2024b). While using CO_2 compensated natural gas is technically climate neutral, it still causes local emissions. Furthermore, a recent analysis has shown that up to 90% of currently traded carbon credits do not deliver meaningful carbon reductions (Greenfield, 2023). According to Bloomberg (2023), both the voluntary and bifurcation scenarios could lead to deceptive decarbonisation efforts by companies as they could offset their CO2 emissions cheaply with low-quality offsets while continuing to invest in fossil fuel based technologies. The persistence of local emissions, coupled with the potential for misleading decarbonisation efforts facilitated by the carbon credit market, may prompt the introduction of more stringent emission policy. One way the government could prevent these issues is by setting a cap on local CO_2 emissions. Such regulations are already being implemented in the transportation sector, restricting access for high-emission vehicles to specific areas (Gemeente Utrecht, 2024a). Vehicles using CO_2-compensated diesel or gasoline are not exempt from these rules, as the primary objective is to reduce local emissions rather than offset total emissions. It is plausible that similar regulations could be extended to other sectors, such as energy and industry, potentially impacting EPU's operations and strategic decisions. Therefore, while the voluntary and bifurcation scenarios technically provide a pathway for EPU to become climate neutral, increasingly stringent regulation poses a risk to the successful implementation of these optimisation results.

Conversely, the hydrogen scenario relies heavily on power-to-heat technologies, with 99% of the energy supply coming from heat pumps. As a result, EPU would not contribute to local emissions in the city of Utrecht. However, the results also indicate that such a system cannot be economically sustained solely by renewable power from solar and wind, forcing EPU to depend on more flexible power sources. By 2035, it is plausible that the Dutch power grid will have integrated sufficient flexible renewable energy capacity, such as power storage, geothermal, or nuclear energy. Nevertheless, it is also likely that a portion of EPU's power imports will originate from non-renewable sources. Should the government implement more stringent climate policies, this reliance on non-renewable power could pose a risk to the successful implementation of these optimisation results.

6.2. GRID CONGESTION

The multi-actor analysis showed that power grid operators currently are facing the challenge of grid congestion due to increasingly unbalanced supply and demand. As a result, it has become increasingly difficult to get a large grid connection. According to Netbeheer Nederland, the waiting list for large grid connections grew to 19,400 applications by February 2024, with approximately half originating from the demand side and the other half from the supply side (2024b). Therefore, relying more heavily on power-to-heat can provide its challenges in the context of grid congestion. As mentioned earlier, the district heating network can both provide a solution to or worsen the problem of congestion depending on system design and dispatch strategy. If EPU wants to successfully rely on power-to-heat in the future it is imperative that these challenges are considered during the implementation of optimisation results.

Successful implementation of power-to-heat (P2H) technology is heavily dependent on the integration of thermal energy storage. This combination enables P2H assets to be dispatched during off-peak hours or periods of supply-side congestion, thereby facilitating demand-side response strategies. By operating P2H assets during off-peak hours and storing the generated thermal energy for later use, EPU can mitigate demand-side congestion caused by its power consumption. Conversely, P2H assets can also support grid stability by absorbing surplus power during supply-side congestion. This benefit becomes especially apparent when considering the PV installations owned by the local community in Utrecht. This dual capability establishes a mutually beneficial relationship between EPU and grid operators. On one hand, EPU contributes to grid stability; on the other, it can capitalize on favourable market conditions. In return, grid operators could offer tariff discounts of up to 65% as outlined in the new ATR85/15 regulation, further incentivizing EPU's role in balancing the grid (Netbeheer Nederland, 2024c).

Eneco has already demonstrated the application of such system thinking in previous projects, with the Ivy Apartments in Nieuwegein serving as a notable example. To address the challenges posed by the long waiting list for large grid connections, the 99 apartments are equipped with a heat pump, and a combination of tank thermal energy storage and aquifer thermal energy storage (Eneco, 2024e). In the summer, the building is cooled using groundwater, which is subsequently warmed and stored underground to satisfy heating demands during the winter. This approach enables the operation of a smaller heat pump, effectively mitigating power grid congestion. Additionally, the inclusion of tank thermal energy storage enhances congestion management by providing short-term load balancing.

In the removal and hydrogen scenarios, the optimisation model recommends a heat pump capacity ranging from 50 to 162 MW. While such capacity might initially seem infeasible due to ongoing congestion issues, it is important to consider that the required grid connection is three times smaller than the heat pump's thermal capacity, thanks to their typical coefficient of performance of three. Currently, EPU already operates two 10 MW E-boilers, resulting in a total power grid connection of 20 MW. It is important to highlight that the advantage of a smaller grid connection relative to thermal output is not observed with E-boilers. With the required grid connection for heat pumps falling between 17 MW and 54 MW, this capacity appears highly feasible from a multi-actor perspective—especially if the proposed demand-side response methods are implemented. It is important to note, however, that such an implementation could adversely impact dispatch flexibility for EPU. While the ATR85/15 contract offers a 65% discount on grid tariffs, which is advantageous for EPU, it also grants grid operators the ability to restrict power supply for up to 15% of the time. As a result, EPU may need to supplement its system with additional fuel-based peak assets to ensure reliability.

Finally, EPU's role in frequency regulation and congestion management within the Dutch power grid is evident through its electricity-generating assets such as the CCGT and battery energy storage. The results indicate that sourcing more than 85% of energy demand from renewable power sources becomes economically unfeasible. Consequently, if EPU transitions to an all-electric system, 15% of its power demand would need to be met by flexible energy sources. However, the optimisation results in the hydrogen scenario, which assume constant grid power availability, suggest a full reliance on P2H. This finding underscores potential challenges not only in achieving climate policy targets, as discussed earlier, but also in frequency regulation. If similar conclusions are drawn by other actors within the Dutch power grid, it could result in a significant reduction in the installation of flexible CCGT capacity, leaving a critical gap in meeting energy demand. Paradoxically, while the findings highlight the need for flexible power capacity, they also suggest that EPU might not install such capacity themselves. This could signal a shift in the future profitability of CCGT assets—from power sales (kWh) to compensation for providing flexible capacity (kW). Thus, implementing an all-electric district heating network (DHN) poses not only regulatory risks but also risks of undervaluing the economic potential of flexible power assets. The multi-actor analysis emphasizes that maintaining some flexible power capacity, currently provided by CCGTs, should remain a key consideration in the design and deployment of large-scale energy systems.

6.3. SPATIAL REQUIREMENTS

To support the energy transition within Utrecht's district heating network, EPU may need additional asset locations across the city. While EPU, the Municipality of Utrecht, and the local community share aligned goals regarding the energy transition, tensions could arise due to competing priorities. The municipality and local community highly value creating and maintaining a livable urban environment, including preserving recreational green spaces. EPU's need for decentralized energy assets throughout the city could conflict with this shared objective. The local community holds significant influence in this matter, as their objections could block the issuance of building permits for new infrastructure. This highlights the importance of EPU designing future-proof, decentralized assets that align with the goals of maintaining and enhancing green urban spaces rather than detracting from them. One effective strategy is to integrate green and biodiverse features into the design of energy assets (Appendix B.7). Research indicates that urban greenery positively impacts community well-being. For example, increased urban greenery has been shown to significantly improve self-reported happiness levels (Veenhoven et al., 2021). Additionally, proximity to green walls has been found to reduce heart rate and blood pressure while boosting α brain wave activity, which is associated with relaxation and improved focus (Ma et al., 2024). Such benefits to the local community could foster support for new asset development in their neighborhoods, reducing opposition to building permits. Moreover, integrating greenery into energy assets aligns with the municipality's biodiversity and environmental goals (Gemeente Utrecht, 2024b). Beyond fostering community approval, these assets can enhance air quality, reduce noise pollution, and improve the urban environment's thermal resilience, creating a mutually beneficial outcome for EPU, the local community, and the city of Utrecht.

7

LIMITATIONS

Throughout this research, various assumptions were made to develop the optimization model, interpret results, and formulate recommendations. While these assumptions were necessary to simplify complex systems and ensure the feasibility of the analysis, they also introduced several limitations. These limitations have implications for the generalizability, accuracy, and applicability of the findings. The goal of this chapter is to outline these limitations and discuss their impact on the study's outcomes. By doing so, it provides essential context for interpreting the results and drawing conclusions, ensuring a balanced and transparent evaluation of the research.

7.1. INPUT DEPENDENCY

The first limitation to discuss is the dependency of the results on the input dataset, including thermal demand, power prices, and fuel prices. Since the optimisation model relies on a single year of thermal demand data—specifically from 2023—the results are applicable only to similar demand profiles. This limitation is particularly relevant for reliability metrics, as the model enforces a constraint ensuring that supply always meets or exceeds demand, effectively achieving 100% energy security in the optimisation results. If future thermal demand deviates significantly from the 2023 profile, the recommendations may no longer generalise to such systems, potentially compromising energy security in cases of higher demand.

The dependency on fuel and power prices presents another key limitation. As the energy transition progresses rapidly, assumptions made in this research about pricing curves may no longer hold. For instance, demand shocks in gas prices, as seen during 2022 due to the Russia-Ukraine war, can drastically alter optimal system design. Moreover, the future trajectory of the Dutch energy infrastructure remains uncertain. Recent shifts in government policy have reintroduced nuclear power as a priority, with plans to sustain the current 485 MW capacity and explore the construction of two additional large nuclear facilities (Rijksoverheid, 2024a). If these plans are realised, the share of nuclear energy in the Dutch energy mix could more than triple to 13% (Rijksoverheid, 2024a). This increase in baseload power generation would likely have a profound impact on the price assumptions used in this study. Finally, power price assumptions are based on Eneco's forecasts of installed renewable energy capacity. Any deviation from these projections—whether through underachievement or overachievement—could significantly influence future power prices and, consequently, the outcomes of the optimisation model.

Additionally, another limitation lies in the relationship between power and natural gas prices. In this research, power prices were forecasted independently of natural gas prices. While this assumption holds in scenarios where the majority of future power generation is sourced from renewables such as wind and photovoltaic (PV) systems, it may not remain valid if the energy transition progresses more slowly than anticipated. In such a scenario, natural gas prices could have a much stronger influence on power prices due to continued reliance on gas-fired power generation. This interdependency could significantly impact the accuracy of the forecasts and, consequently, the optimisation results.

Another limitation related to the model input is the exclusion of auxiliary power markets. In this research, only the day-ahead power market was considered. However, in real-world operations, revenue-generating assets such as BES systems and CCGTs derive a significant portion of their profitability from auxiliary markets, including imbalance and frequency regulation markets. By omitting these markets, the model may underestimate the economic performance and potential revenue streams of these assets, thereby affecting the optimisation outcomes.

Finally, this study does not include a sensitivity analysis of individual asset parameters. As discussed during the optimisation design phase, a single-layer MILP algorithm was chosen to run the optimisation model. While this approach guarantees finding the global optimum, it is computationally intensive. Given the extensive number of assets included and the substantial amount of input data required per asset, conducting a comprehensive sensitivity analysis was computationally infeasible within the scope of this research. Consequently, the specific impact of variations in individual asset parameters remains insufficiently explored.

7.2. MODELLING ASSUMPTION

In addition to the dependency on input variables, several assumptions were made during model development. One notable limitation is the implementation of the ATES system, which was modeled without explicitly including a heat pump. Although the model accounts for the power costs associated with heat pump operation within its operational expenditures, these costs are approximated as a percentage of the capital expenditures, based on Eneco's prior research into high-temperature ATES systems. Consequently, the ATES system's power consumption is calculated using a fixed average power price rather than leveraging variable market pricing, which may impact the accuracy of the results.

Another assumption in the model is that asset capacities are treated as continuous variables. While this approach significantly improves solution time and provides valuable insights, it may present challenges when implementing results exactly as suggested, as real-world investments often involve standardized capacities for assets such as CCGTs, which are only available in specific sizes.

While the model accounts for Utrecht's various districts to accurately represent thermal losses during transport, the recommendations in this research are based on the assumption that EPU's network operates as a single location. This simplification highlights the need for future research into the optimal placement of assets within the network.

Finally, the model assumes 100% operational availability of all assets. In practice, however, assets may experience downtime due to unexpected failures or scheduled maintenance. By not accounting for such downtime, the model's recommendations could face challenges in guaranteeing energy security if asset failures were to coincide with periods of high demand.

7.3. TECHNOLOGICAL ADVANCEMENTS

During the system design phase, this study focused on identifying commercially available and economically competitive technologies that could be implemented at scale within EPU's district heating network. The accelerating pace of the energy transition in recent years has driven rapid innovation in energy technologies. A notable example is the exponential decline in battery energy storage costs, spurred by the mass adoption of electric vehicles. This rapidly evolving technological landscape introduces a key limitation: technologies currently excluded from this study may become commercially viable in the near future.

One significant area affected by this limitation is the selection of thermal energy storage systems. At present, only sensible thermal energy storage systems are deemed commercially viable for large-scale deployment. However, latent and thermochemical thermal energy storage systems, due to their advantageous properties, are gaining substantial attention in energy research. If ongoing advancements address their current challenges, these technologies could emerge as superior TES solutions, fundamentally altering the system design framework considered in this research.

Another potential disruption could arise on the energy supply side. This study incorporates combined cycle gas turbines (CCGTs), a proven and widely adopted technology for combined power and heat production. CCGTs offer operational flexibility, capable of utilizing a range of fuels such as natural gas and hydrogen. However, hydrogen adoption is still in progress, and the planned hydrogen pipeline network does not include Utrecht due to its limited industrial activity, complicating hydrogen adoption in the region (Gasunie, 2024).

A promising alternative to CCGTs is the reversible Solid Oxide Fuel Cell (SOFC). Like combined cycle turbines, SOFCs can utilize diverse fuels, including natural gas and hydrogen, to produce heat and power with an efficiency of 90% (Siemens, 2023). However, SOFCs offer an additional advantage: their reversible nature enables them to function as a key component in hydrogen energy storage systems. This means that SOFCs can not only generate power and heat from hydrogen but also produce hydrogen from power (Siemens, 2023). Such dual functunality would provide enourmous benefits to EPU. Especially considering the multi-actor environment, SOFCs could provide a promising combined heat and power source that can contribute significantly to congestion management, creating hydrogen during supply-side congestion and subsequently using it to generate power and heat during demand-side congestion. While this technology is not yet commercially available, significant ongoing research suggests that it could become viable in the near future, offering a transformative solution for district heating networks and broader energy systems.

8

Conclusion and strategic recommendations

The presented research aimed to identify an effective capacity optimisation approach in hybrid renewable energy systems from a systems engineering perspective and apply it to Eneco's district heating network in Utrecht. This chapter presents the conclusion of the research and follows with strategic recommendations based on the findings. Thereby, the objective of this chapter is to answer the main research question:

What is an effective approach to capacity optimisation in renewable energy systems that integrate thermal and power sources with hybrid energy storage?

8.1. Conclusion

The presented research adopts a systems engineering perspective on optimization in hybrid energy systems, highlighting the importance of integrated system analysis from a multi-actor, technological, and institutional perspective. The first step in the optimisation approach is to define the system design guided by multi-actor analysis. From the multi-actor analysis, it has become apparent that Energy Production Utrecht (EPU) is involved in a complex decision making process influenced by multiple high-power, high-interest actors; the municipality of Utrecht, the local community, and grid operators. The outcome of this analysis, showing both opportunities for cooperation and threats, constrains the technological design space. For example, although recent research suggests that geothermal energy is likely accessible in the city of Utrecht, opposition from the local community makes successful implementation unlikely (Böker & Leo, 2021). The system design space is further constrained by the already existing technological landscape and its associated requirements such as temperature, thermal carrier, dispatch flexibility, and storage duration. Based on the analysis, we conclude that the following assets are suitable for implementation in EPU's district heating network: combined cycle gas turbines, peak boilers, heat pumps, e-boilers, and energy storage solutions. The energy storage options include aquifer thermal energy storage (ATES), tank thermal energy storage (TTES), solid-state thermal energy storage (SSTES), and battery energy storage (BES). These assets can be directly implemented in the district heating network and can al be sustainable sources of heat and/or power. Additionally, EPU will need a power grid connection to supply its power-to-heat assets and/or to sell excess generated power, as well as a fuel connection to supply its fuel-based assets.

Following the system design phase, the process moves into the optimization design phase, where the objectives, decision variables, and optimization algorithm are defined. From the reviewed literature, we can identify three primary objectives in energy systems: reliability, cost, and emissions. For EPU, all three objectives are crucial. First, maintaining low costs is essential for ensuring profitable business operations. Reliability is equally important, as EPU is solely responsible for supplying thermal energy to households in Utrecht; any supply interruption would leave these households without heating and hot water. Finally, emissions reduction is a key priority for EPU, aligning with their goal to achieve “renewable energy for everyone” (Eneco, 2024f). To reduce computational expense associated with multi-objective optimization, the emissions and reliability objectives have been translated into constraints, allowing the objective function to focus solely on cost. The objective of minimum cost, is achieved through adjustment in the decision variables. From the reviewed literature, we identified three primary decision variables; asset capacity, dispatch strategy, and network location. For EPU, the required asset capacities emerge as the most relevant decision variable. Finally, the optimisation algorithm is selected. From the reviewed literature, we can identify two algorithm approaches: single-layer optimisation, and dual-layer optimisation. In single-layer optimization, both asset capacity and dispatch strategy are optimized simultaneously using mixed integer linear programming (MILP), which ensures a global optimum. In contrast, dual-layer optimization addresses these components sequentially, defining a rule-based dispatch strategy before applying a heuristic algorithm, such as genetic or particle swarm optimization, to determine asset capacities. While dual-layer optimization achieves only a near-optimal solution, it offers faster solution times than the computationally intensive MILP approach. The system design for EPU’s district heating network is complex, involving multiple assets for both electrical and thermal energy, further complicated by seasonal variations in energy flows. Therefore, it is unlikely that a rule-based dispatch strategy would accurately reflect the optimal dispatch, potentially impacting the results negatively. For this reason, the presented optimisation model makes use of the MILP algorithm.

Following the optimisation design, the system design must be converted to a functional optimisation model. The identified system components must be modelled given available information and the data that functions as input is collected. In the case of EPU’s district heating network, input data includes the thermal demand, power prices, and fuel prices. The optimization model for EPU is developed in Calliope, an open-source Python tool that leverages the widely used Pyomo optimization package as its back-end while organizing the coding process into a more intuitive structure. Following model development the optimisation is performed across a range of scenarios. Two of the primary data inputs, power prices and fuel prices, are combined in different configurations to create a total of twelve scenarios.

Following optimisation, the optimisation results are analysed for their operational performance. According to Zheng et al. (2018) it is important that simulation techniques are used to evaluate the reliability of optimisation results by creating new data from observed probability distributions. Therefore, we generated two years of synthetic data based on probabilistic patterns observed in the 2023 thermal demand data. Analysis of operational performance of the optimisation results across this dataset shows the loss of heat supply probability (LHSP) ranging from 0.023% to 0.067%. Concluding that optimisation alone, does not guarantee performance across varying demand inputs. Therefore, additional peak capacity should be added to the optimised asset capacity results to ensure operational reliability. Furthermore, we can conclude that as the operational power-to-heat fraction increases, the required capacity of renewable energy sources (RES) also rises. The results indicate that up to an operational power-to-heat fraction of 85%, it is economically feasible to meet the entire power demand with renewables. However, beyond this threshold, the necessary RES capacity increases sharply, rendering full reliance on renewable power economically unfeasible.

Additionally, the comparative performance of two model simplification techniques, k-means clustering and masked time resolution adjustment, has been evaluated. K-means clustering offers a substantial 98.17% reduction in solution time. However, due to reduced data accuracy, this method negatively impacts operational performance, with the loss of heat supply probability (LHSP) increasing from 0.056% to 0.500%, representing a 792.86% increase. Conversely, the masked time resolution adjustment method yields a lower solution time reduction of 91.58% but more closely mirrors the results from full optimization. Consequently, operational performance improves, with an LPSP of 0.054%, a 3.57% improvement. Concluding that masked time resolution adjustment presents a more favourable trade-off between solution time and model performance.

Finally, we evaluated how scenario inputs affect optimisation outcomes with the use of regression models. To quantify the scenario inputs for average power and fuel prices, we used a power/fuel price ratio (PF ratio). The results show that:

- As the PF ratio increases, meaning that power becomes more expensive relative to fuel, the reliance on power-to-heat assets reduces. Conversely As the PF ratio increases, the reliance on fuel-based assets increases.
- As the PF ratio increases, the levelised cost of heat decreases due to the CCGT's ability to generate revenue in the power market.
- The Loss of Heat Supply Probability (LHSP) is a function of thermal peak capacity and flex capacity as a percentage of peak demand, with LHSP decreasing as these capacities increase.

Concluding, this research shows a systematic approach to optimisation in hybrid renewable energy systems in five steps; multi-actor analysis, system design, optimisation design, model development, and analysis of results. Each of these steps has adopted techniques from the reviewed scientific literature, presenting an integrated approach to optimisation from a systems engineering perspective.

8.2. STRATEGIC RECOMMENDATION

In addition to addressing the main research question and identifying an effective approach to optimizing hybrid energy systems, this research offers strategic insights for EPU. Five primary insights have been identified surrounding: The multi-actor environment, capacity distribution, district heating network temperature, seasonal storage, and required asset capacities. Each of these insights will be discussed in more detail in this chapter.

8.2.1. MULTI-ACTOR ENVIRONMENT

Chapter 6, interprets the optimisation results through a multi-actor lens, addressing implications for emissions policy, grid congestion, and spatial requirements. It showed that scenarios relying fully on CO_2-compensated natural gas achieve low costs but face political and regulatory challenges due to persistent local emissions and concerns over low-quality carbon offsets. In contrast, a power-to-heat (P2H) based system minimizes local emissions but depends on non-renewable power imports, which may conflict with future climate policies. Furthermore, Power-to-heat (P2H) technologies come with the challenge of contributing to grid congestion. Combining them with thermal energy storage, is vital for managing this congestion by enabling demand-side response and stabilizing power supply. Lessons from projects like the Ivy Apartments demonstrate the feasibility of integrating P2H within congested grids. However, reliance on all-electric systems demands flexible power sources and raises concerns about underutilized potential of flexible fuel-based assets like CCGTs.

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To ensure the successful implementation of optimisation results, it is essential for EPU to consider these factors. The most resilient system design, from a multi-actor perspective, involves implementing a hybrid approach that incorporates both fuel-based and P2H assets. By avoiding reliance on a fully electric system, EPU can draw power from renewable energy sources while maintaining operational flexibility through fuel-based assets. This flexibility, enabled by the use of diverse fuels, also ensures resilience against potential changes in climate policy. Moreover, the multi-actor analysis highlights that resilience is not solely dependent on fuel-to-heat technologies but also on fuel-to-power assets, such as combined cycle gas turbines. These technologies play a crucial role in managing grid congestion and supporting frequency regulation within the Dutch power grid, while simultaneously providing a flexible thermal source for the district heating network. Concluding that a hybrid system design, integrating power-to-heat, fuel-to-heat, and fuel-to-power assets, offers the most resilient implementation option within a complex regulatory and multi-actor environment. This approach ensures flexibility, adaptability to policy changes, and alignment with broader energy and grid stability goals.

8.2.2. CAPACITY DISTRIBUTION

Another insight is that, although this study presents the optimization outcomes as single assets, their capacity could be distributed across the district heating network (DHN) in various configurations. The model assumes that CCGT operation always occurs at maximum efficiency, regardless of capacity factor. However, in practice, a CCGT's efficiency declines the further it operates from its designed full load (Koeneke, 2024). Therefore, while incurring higher capital expenditures, installing multiple smaller CCGTs rather than one large CCGT based on observed load factors could increase efficiency, decrease net operational expenditures, and improve the lifecycle business case.

Furthermore, the dispatch of thermal assets is highly complex due to asset characteristics, varying thermal demands across regions, and transportation time. The most effective distribution approach is to establish a decentralized DHN. By positioning assets at different heat transfer stations instead of at EPU, several benefits can be achieved. Firstly, decentralization reduces transport time by bypassing the primary grid, thus lowering thermal losses during transport. Moreover, this reduction in transport time allows for a shorter forecasting window for thermal demand, simplifying asset dispatch. Additionally, the secondary grid operates at a lower temperature, enhancing the efficiency of assets like heat pumps. However, decentralized operation also limits thermal load distribution: assets placed in secondary grids can only supply thermal energy to their specific networks, whereas assets in the primary grid can support all secondary networks. To achieve a decentralised district heating network, EPU should conduct research into spatial availability and available power grid capacity at secondary locations.

8.2.3. LOWERING TEMPERATURE

Lowering the temperature of the primary grid is an alternative approach that can capture many benefits of decentralized operation while limiting its drawbacks. Although this approach wouldn't reduce transport duration, it would decrease thermal losses during transport. Lowering the primary grid temperature would also increase the efficiency of heat pumps connected to it while allowing these assets to supply heat across all secondary grids. Another advantage of temperature reduction is that it enables TTES systems to be located in primary grid locations, extending their reach across the network. Additionally, it allows ATES systems to operate without a heat pump by using heat exchangers instead, reducing system costs. However, a temperature reduction would also decrease grid capacity, as thermal demand is currently met through temperature regulation, potentially requiring additional peak assets in secondary locations. Therefore, it is essential for EPU to conduct further research into the possibilities of temperature decrease.

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8.2.4. SEASONAL STORAGE

Another key insight is the critical role of affordable and efficient seasonal thermal energy storage for the success of district heating networks. Implementing large-scale seasonal thermal energy storage enables EPU to capitalize on seasonal fluctuations in energy markets and reduce pricing risk. The average optimized ATES storage capacity is 78 GWh, which, at a capacity of 100 MW, equates to 782 hours or approximately 33 days of continuous full-load operation. Therefore, EPU should initiate a pilot project for implementing large-scale seasonal thermal energy storage using high temperature ATES. If such a pilot project were to yield unexpected negative results, it is important to acknowledge that decentralized low-temperature ATES, as implemented in the Ivy apartments, could still play a significant role in meeting overall thermal demand. Additionally, unsuccessful outcomes from the pilot would justify further exploration of alternative large-scale seasonal thermal energy storage technologies.

8.2.5. ASSET CAPACITIES

Finally, the evaluation of the twelve scenario results reveals a diverse range of asset mixes, spanning from a complete reliance on fuel-based assets to a full dependence on P2H assets. This variation raises the critical question: which scenario should EPU plan for? Drawing on insights from the multi-actor analysis, we recommend implementing a hybrid system design. This approach aligns with our analysis regarding the carbon market, where the prevalence of low-quality offsets may prompt regulatory changes favouring a shift towards the removal scenario.

Therefore, the recommendation for EPU based on this research is to implement the hybrid results from the removal scenario with heat pump capacity ranging from 50 MW_{th} to 132_{th} MW, CCGT capacity ranging from 177 MW_e to 49 MW_e, and peak boiler capacity ranging from 32 MW_{th} to 54 MW_{th}. Additionally, EPU should incorporate thermal energy storage, including ATES with a capacity of 100 MW_{th} and a storage capacity between 64 GWh_{th} and 132 GWh_{th}, as well as TTES with a capacity ranging from 42 MW_{th} to 52 MW_{th} and a storage capacity between 259_{th} MWh and 318 MWh_{th}. Finally, we would like to reaffirm that the optimisation model is based on the assumption of 100% operational availability of assets. As such, the recommendations provided serve as a baseline system design. To guarantee energy security in the event of asset failures or maintenance, it is crucial to incorporate additional peak capacity into the system.

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Epilogue

During my MSc dissertation on optimization in renewable energy systems, I encountered numerous opportunities for both professional and personal growth. One of the most significant areas of development has been my in-depth understanding of district heating networks (DHNs) and optimisation problems. Through my research, I uncovered an unexpected yet crucial insight: DHNs have a substantial role to play in alleviating grid congestion, a factor I had not anticipated at the beginning of my research journey.

Beyond technical learning, this dissertation process has been a period of personal growth. It allowed me to connect and apply a wide range of skills and knowledge gained throughout my MSc program, unifying them into a single project. Additionally, my experience working within an organization, interacting with colleagues, and presenting complex concepts effectively to different audiences helped improve my communication skills, an area I have greatly valued developing.

The broader implications of this research for the energy sector became increasingly evident throughout the project. My findings indicate that a system entirely reliant on direct power from renewable energy sources (RES) is economically unfeasible, largely due to the intermittent nature of RES. However, by incorporating storage solutions and fuel sources—such as green hydrogen generated from RES—the model demonstrated that large-scale renewable energy systems can achieve operational efficiency and sound economic results. For Utrecht specifically, the findings suggest that achieving a carbon-neutral DHN by 2035 is feasible and would contribute significantly to emission reduction targets in the region.

Looking forward, the research in this field is likely to evolve alongside technological advancements that influence system design. For example, high-temperature fuel cells could eventually take over the functions of combined cycle gas turbines (CCGTs), while also providing flexibility in the fuels they utilize. These reversible technologies can create power and heat from fuel and, conversely, generate fuel (such as green hydrogen) from power. Although not currently economically viable, such technologies could reshape the design and operation of renewable energy systems in the future. Additionally, rapid changes in energy policies, as demonstrated by the recent WcW (Law on Collective Heat) and ATR85/15 regulations on power grid availability, reflect the evolving regulatory landscape that will continue to shape system design and operational strategies.

It is also important to acknowledge the limitations of this study, which naturally prompt areas for future research. For instance, the research did not incorporate a detailed network analysis to identify optimal locations within the DHN for distributed assets. Such an analysis would enhance our understanding of how to maximize the network's efficiency and potential for distributed generation, indicating a valuable direction for further study.

Finally, I would like to extend my deepest gratitude to my supervisors from TU Delft and Eneco, as well as my extended colleagues at Eneco. Their invaluable insights and guidance have greatly enriched this research and contributed immensely to my professional and personal development.

GLOSSARY

The aim of this chapter is to identify and further explain terms used in the research.

RES: Renewable Energy Sources (RES) often refer to electricity generated from renewable sources such as wind and photovoltaic. However, the term can also encompass other renewable energy sources, including geothermal energy, biomass, and more.
ESS: Energy Storage Systems (ESS) refer to any technology capable of storing energy. The storage medium can vary, encompassing electrical, thermal, or mechanical energy forms.
EPU: Enery Production Utrecht (EPU) is the subsection of Eneco responsible for operation of the district heating network in Utrecht

DHN: District Heating Networks (DHNs) are networks that directly supply thermal energy to households. Additionally, the study mentions District Heating and Storage Networks (DHSNs) which refer to DHNs that also include thermal energy storage.

TES: Thermal Energy Storage (TES) refers to storing energy in the form of heat. Within the TES field, several technologies have been identified, including Aquifer Thermal Energy Storage (ATES), Solid-State Thermal Energy Storage (SSTES), Tank Thermal Energy Storage (TTES), and Molten Salt Thermal Energy Storage (MSTES).

P2H: Power-to-heat (P2H) technologies can convert power directly into heat. Implementations of P2H include Heat Pumps (HPs) and Electrode Boilers (E-boilers).

F2H: Fuel-to-Heat (F2H) technologies convert various fuels, such as natural gas or hydrogen, directly into heat. Examples of F2H implementations include Combined Cycle Gas Turbines (CCGTs) and peak boilers. CCGTs could also be classified as Fuel-to-Power (F2P) technologies, as they generate both heat and power from fuel.

LCOE: The Levelized Cost of Energy (LCOE) represents the cost per unit of energy, calculated by considering all expenditures and energy generated over the system's lifetime. In this research, the Levelized Cost of Heat (LCOH) is also referenced, applying the same concept specifically to thermal energy.

LPSP: The Loss of Power Supply Probability (LPSP) is a measure of operational reliability, representing the percentage of energy demand that could not be met. In this research, the Loss of Heat Supply Probability (LHSP) is also referenced, applying this concept specifically to thermal energy.

A

Appendix A: Data requirements

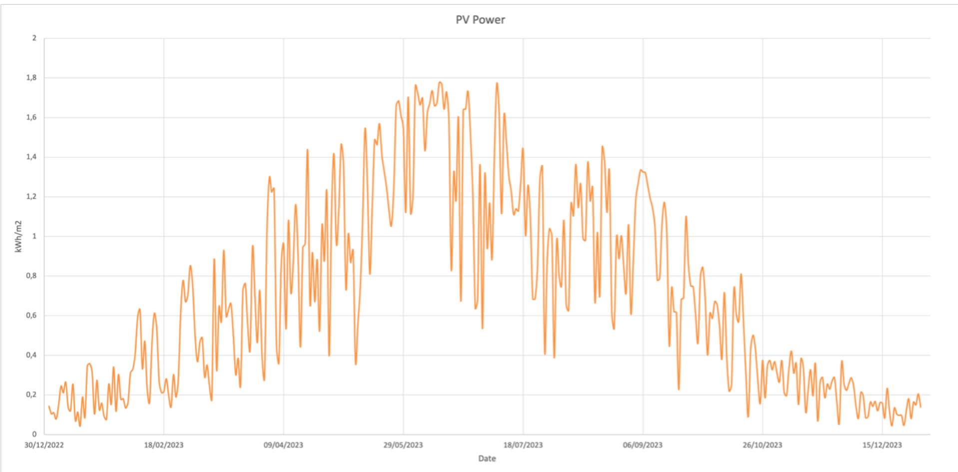

Figure A.1: Photovoltaic generation profile in kWh/m^2 for 2023

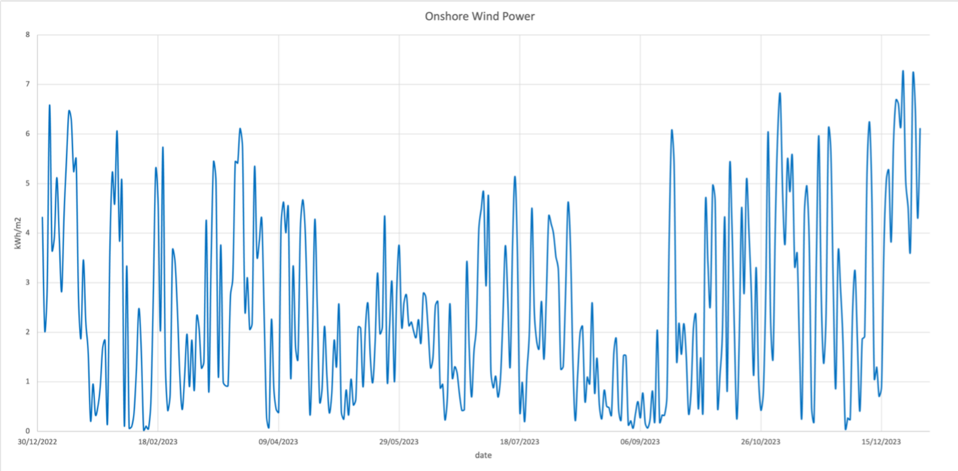

Figure A.2: Onshore wind power generation profile in kWh/m^2 for 2023

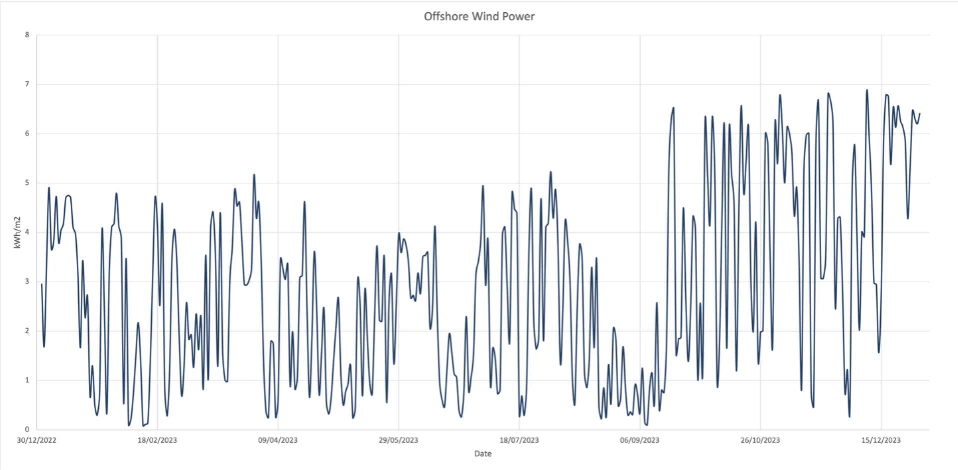

Figure A.3: Offshore wind power generation profile in kWh/m^2 for 2023

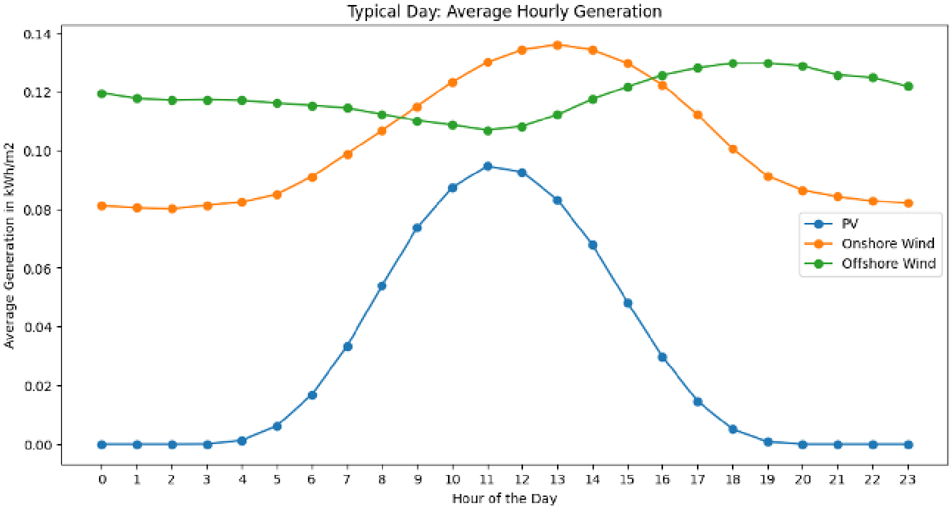

Figure A.4: Average hourly generation of PV, offshore wind, and onshore wind in kWh/m^2 for 2023

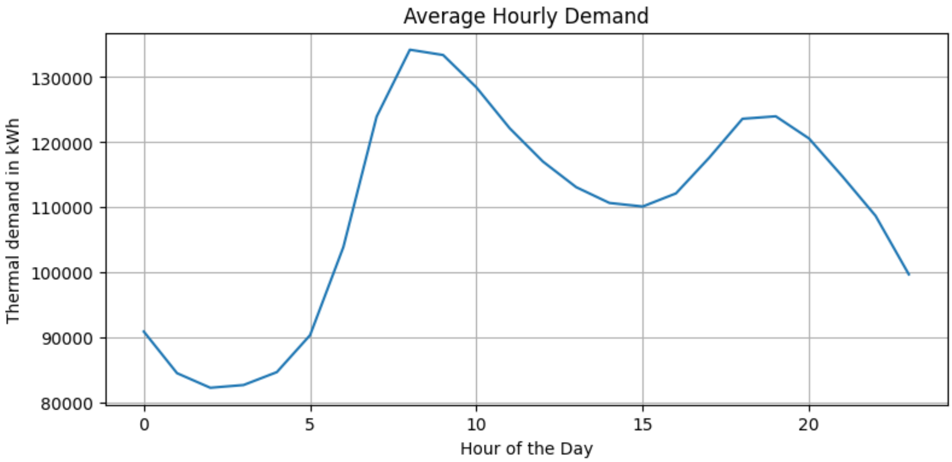

Figure A.5: The average daily thermal demand on an hourly time frame in 2023

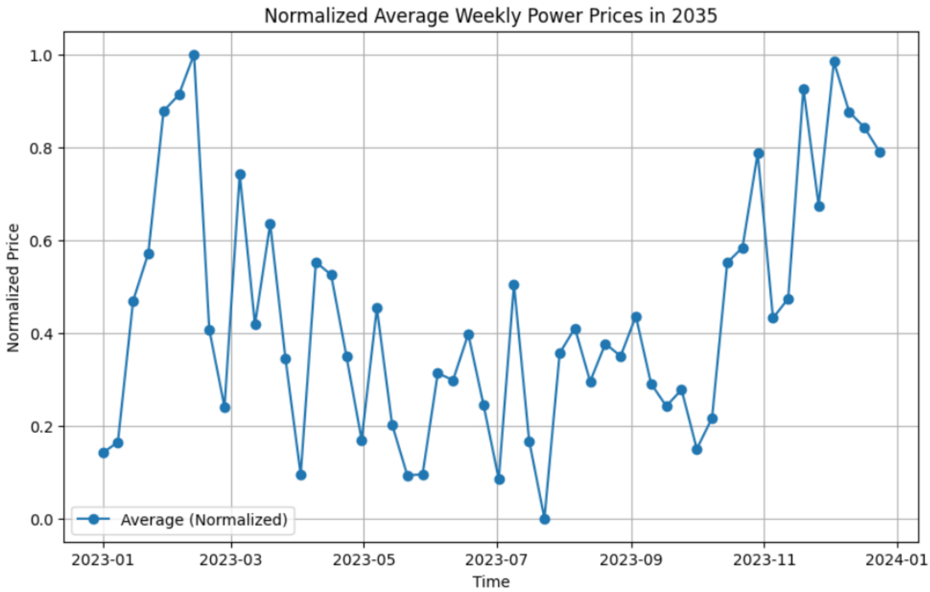

Figure A.6: Normalized average of weekly power prices in 2035, calculated across all scenarios.

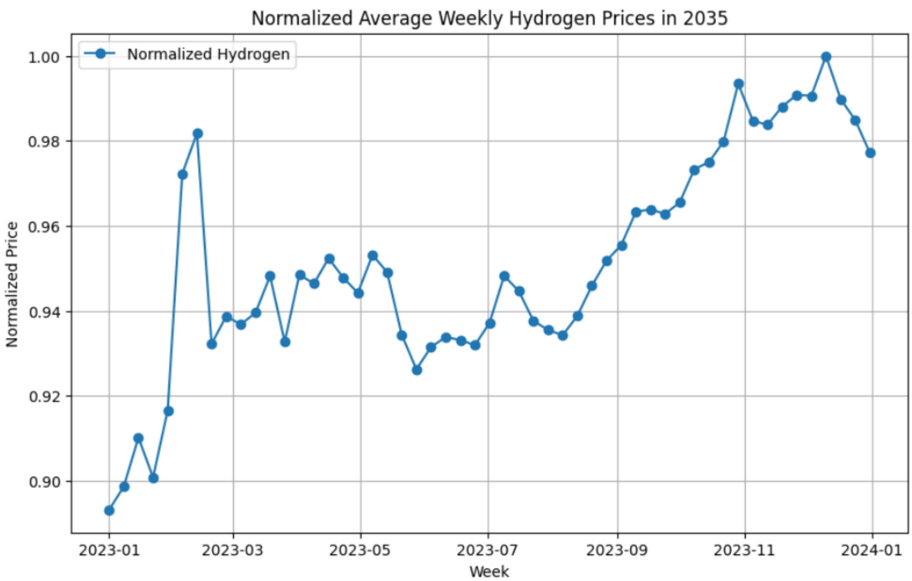

Figure A.7: Normalised average weekly hydrogen prices for 2035

B

Appendix B: Multi-actor analysis

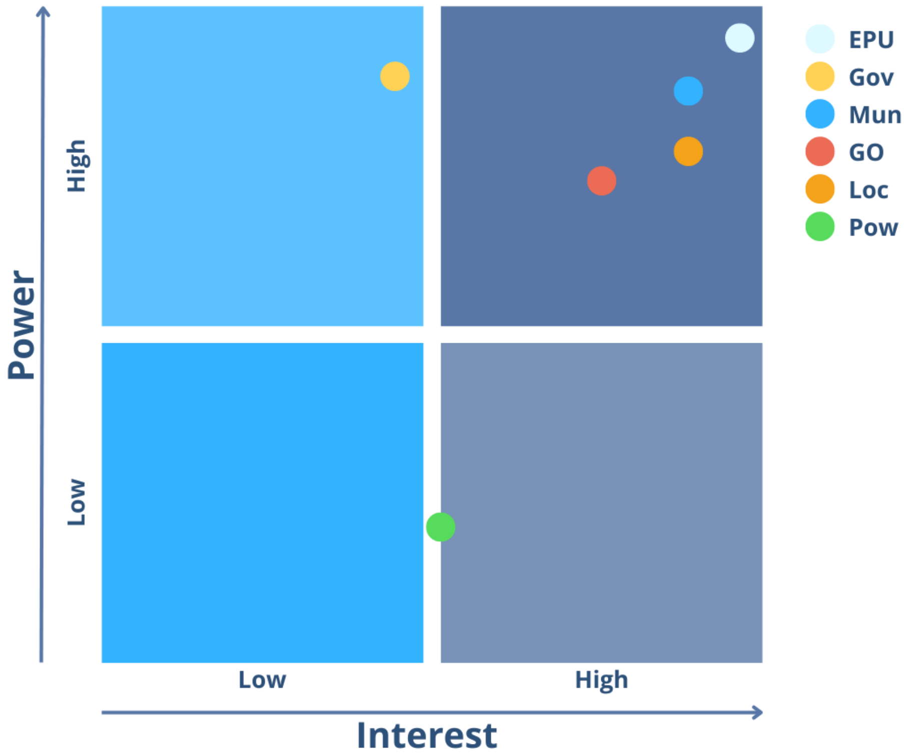

Figure B.1: A visual representation of the power and interest of different actors in the decision-making process, including EPU, the national government (Gov), the municipality of Utrecht (Mun), grid operators (GO), the local community (Loc), and energy companies (Pow).

B

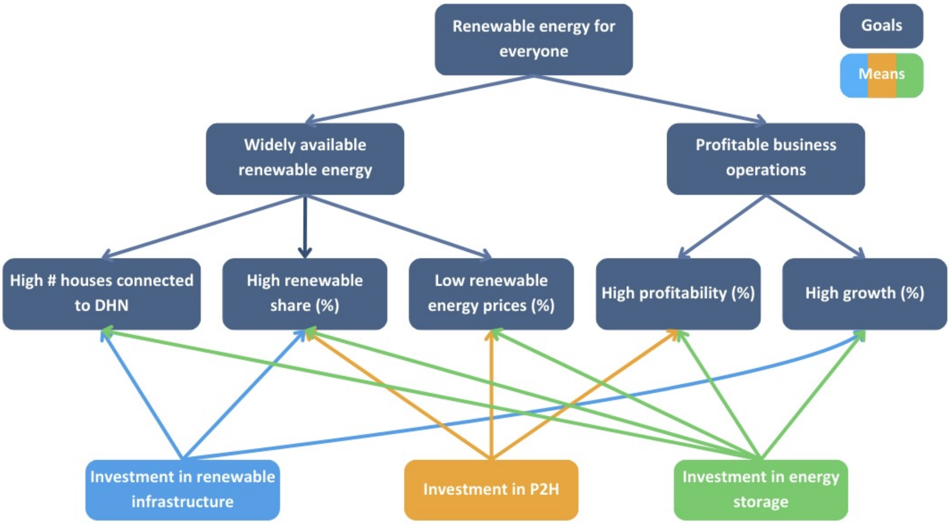

Figure B.2: The goal tree for Energy Production utrecht and the means to achieve its goals.

B

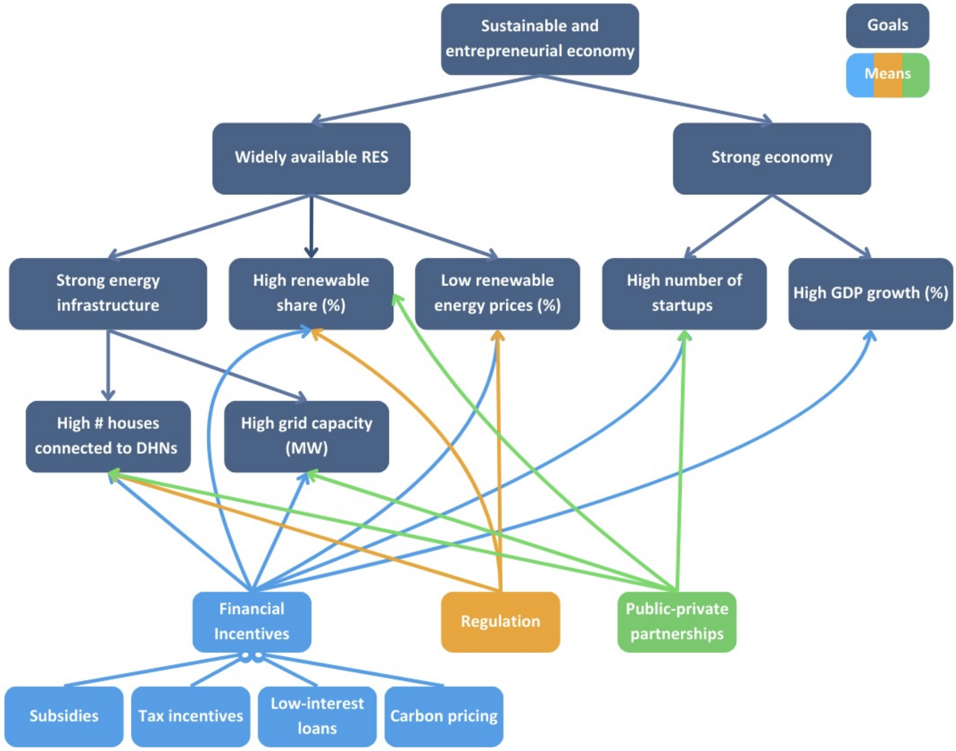

Figure B.3: The goal tree for the Ministry of EZK and the means to achieve those goals in the context of the energy transition.

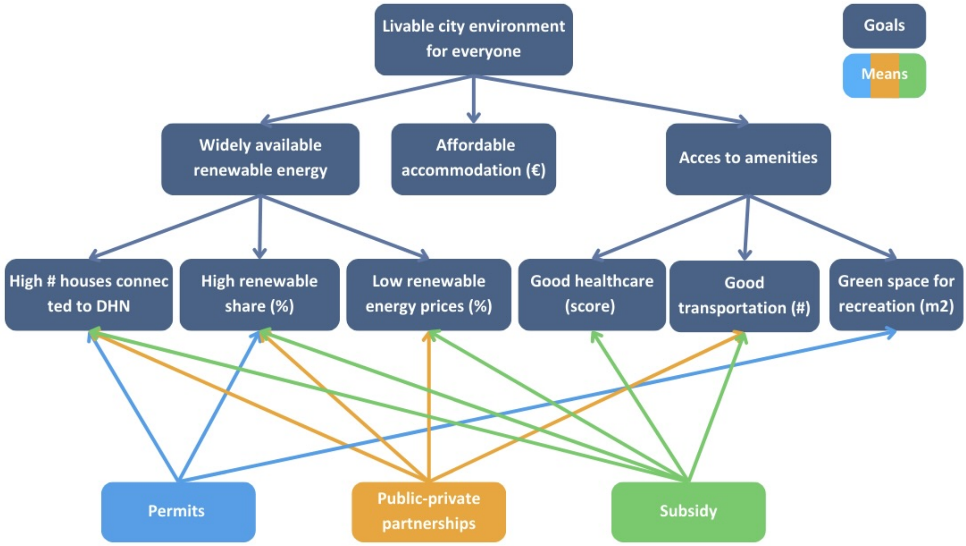

Figure B.4: The goal tree for the municipality of Utrecht and the means to achieve its goals

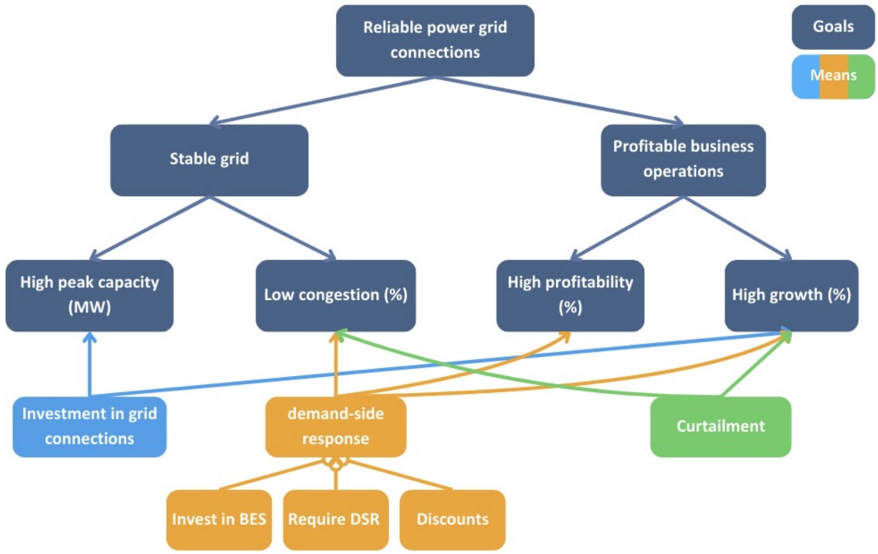

Figure B.5: The goal tree for the grid operators and the means to achieve their goals

B

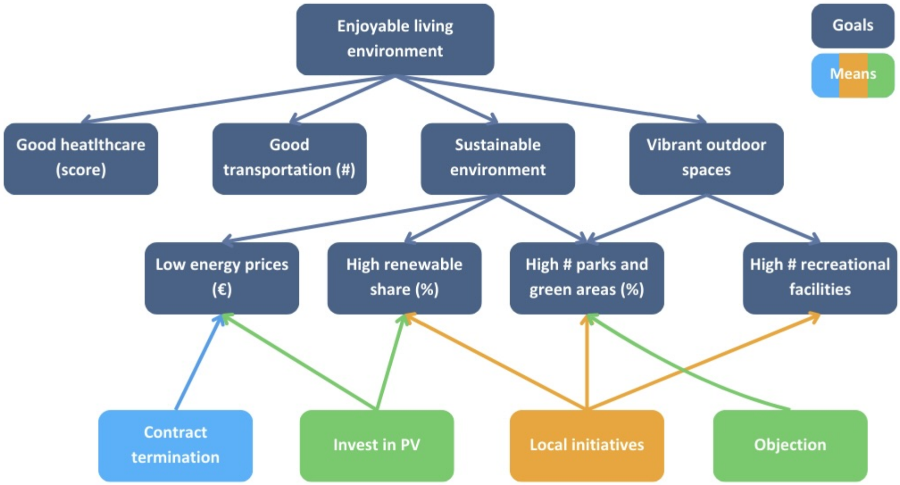

Figure B.6: The goal tree for the local community and the means to achieve their goals.

Figure B.7: Illustration of a distributed energy asset, specifically a tank thermal energy storage system, featuring an integrated green wall for enhanced environmental and aesthetic benefits.

C

Appendix C: Analysis of results

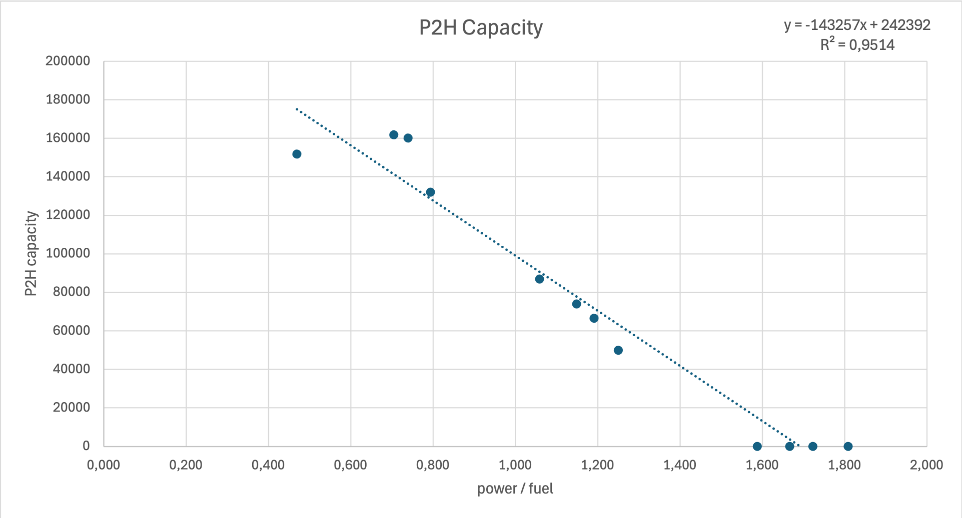

Figure C.1: A linear regression analysis with the total power-to-heat (P2H) capacity as its dependent variable and the power/fuel price ratio as its independent variable.

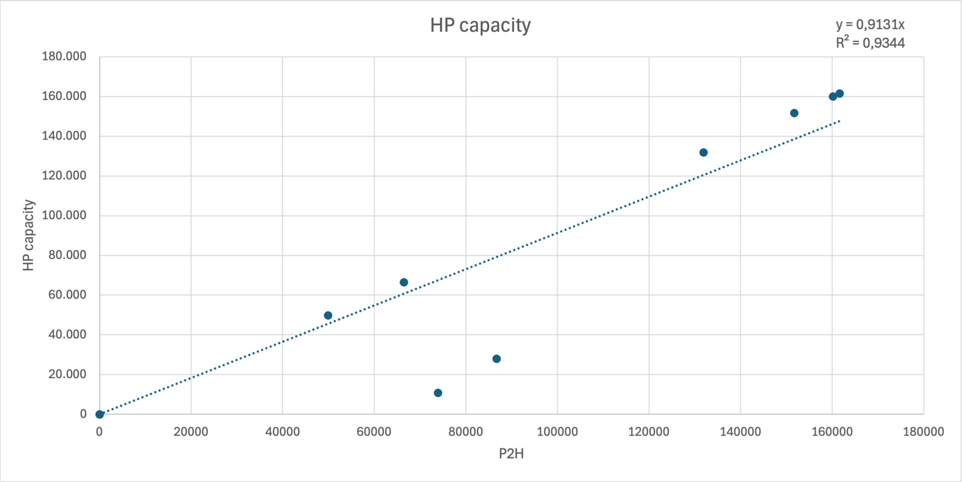

Figure C.2: A linear regression analysis with the total heat pump capacity as its dependent variable and the power-to-heat capacity as its independent variable.

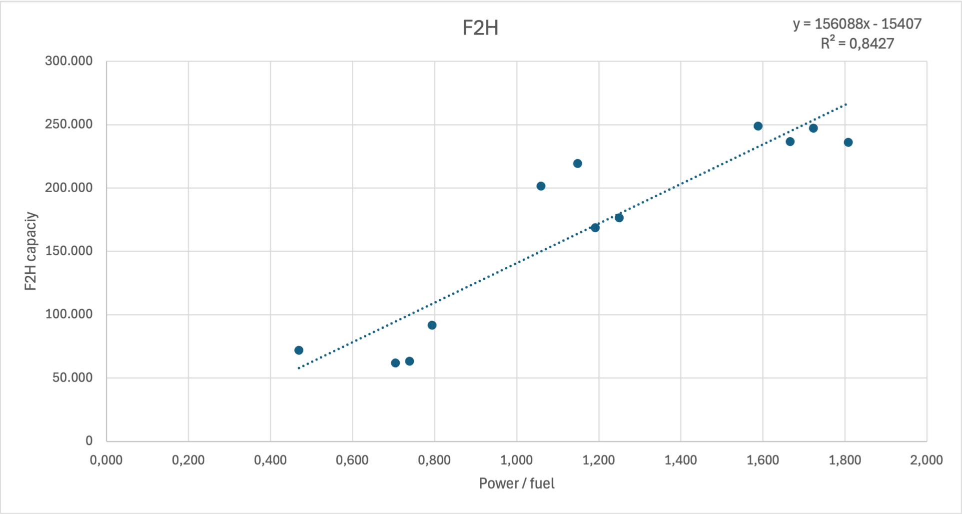

Figure C.3: A linear regression analysis with the total Fuel-to-heat (F2H) capacity as its dependent variable and the power/fuel price ratio as its independent variable.

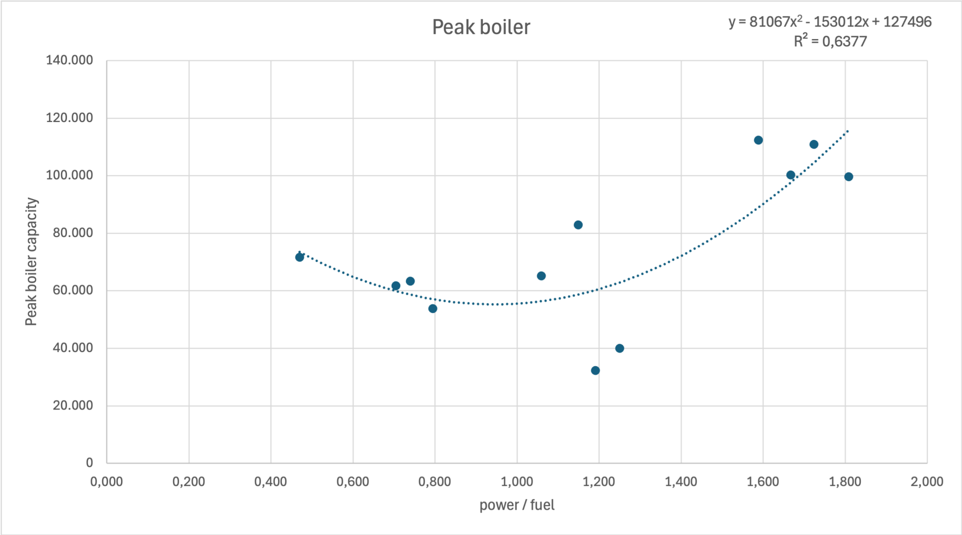

Figure C.4: A linear regression analysis with the total peak boiler capacity as its dependent variable and the power/fuel price ratio as its independent variable.

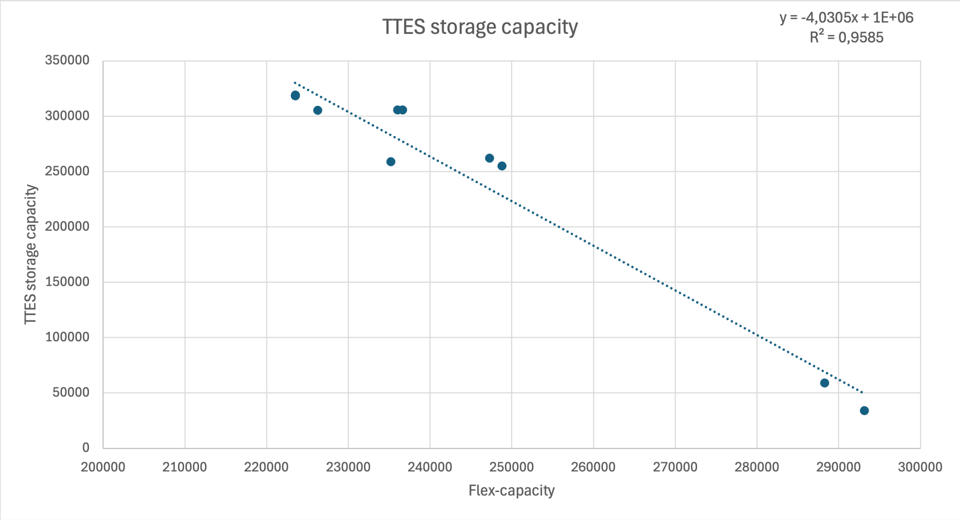

Figure C.5: A linear regression analysis with TTES storage capacity as its dependent variable and the thermal flex-capacity as its independent variable.

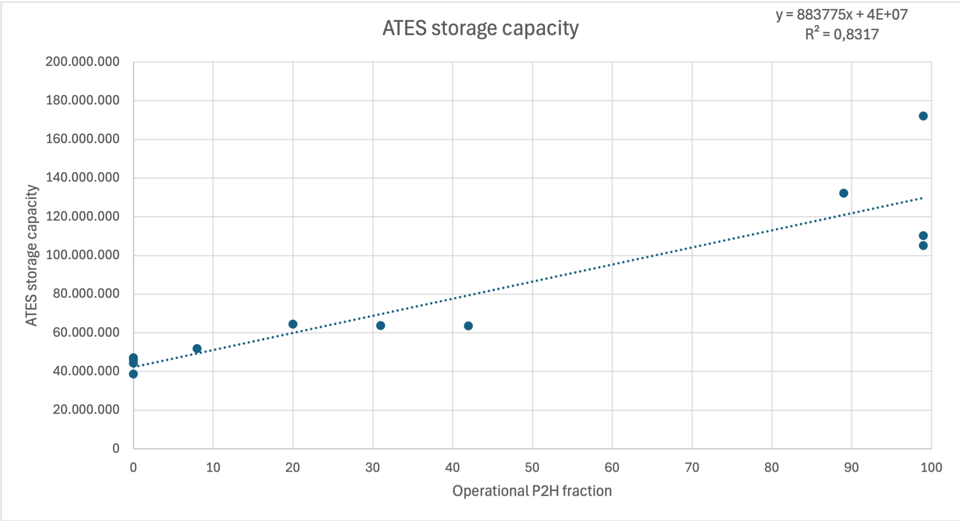

Figure C.6: A linear regression analysis with ATES storage capacity as its dependent variable and the operational P2H fraction as its independent variable.

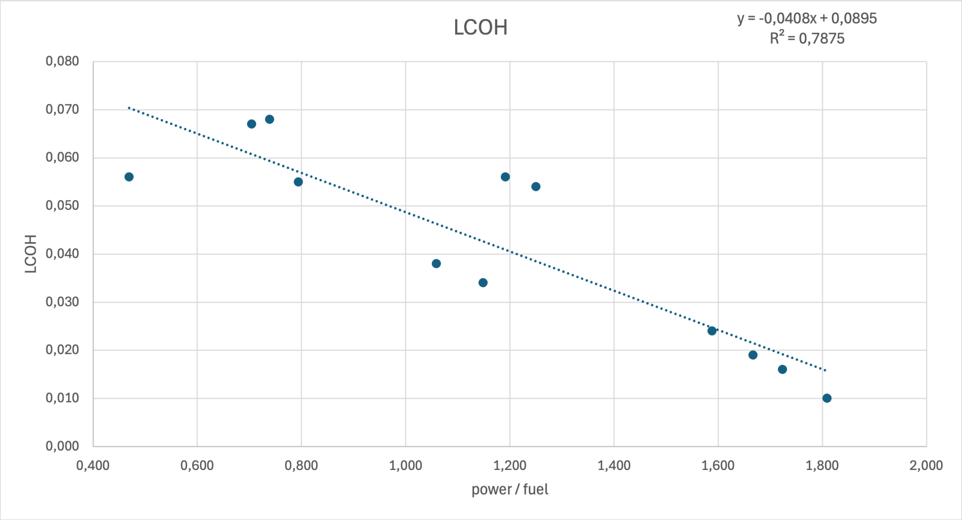

Figure C.7: A linear regression analysis with LCOH as its dependent variable and the power / fuel price ratio as its independent variable.

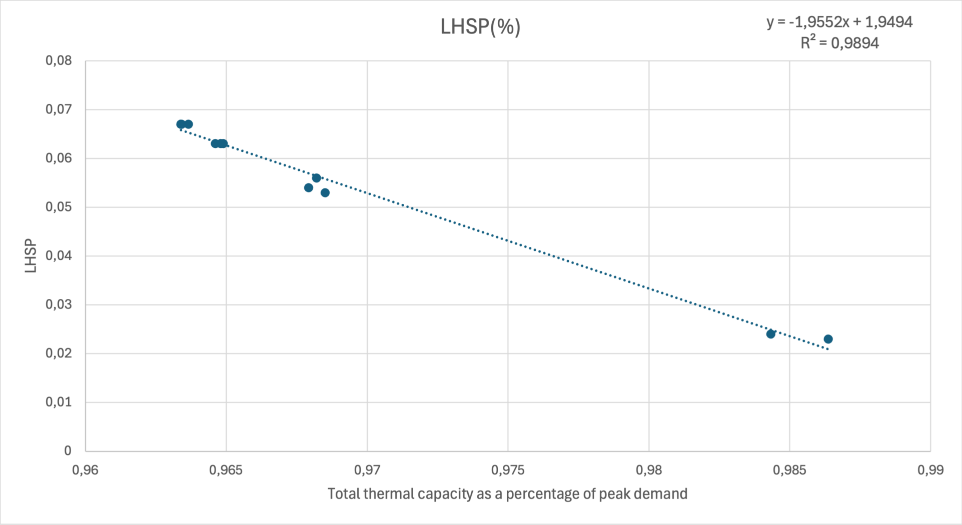

Figure C.8: A linear regression analysis with loss of heat supply probability (LHSP) as its dependent variable and total thermal capacity as a percentage of peak demand as its independent variable.

Regression Statistics	
Multiple R	0,997303329
R Square	0,99461393
Adjusted R Square	0,993417025
Standard Error	0,001284012
Observations	12

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	0,002740078	0,001370039	830,9885421	6,17624E-11
Residual	9	1,48382E-05	1,64869E-06		
Total	11	0,002754917			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	1,340283552	0,210849215	6,356597308	0,000131844	0,86330949	1,817257614	0,86330949	1,817257614
cap % peak	-1,268511247	0,236747579	-5,358074843	0,000457469	-1,804071478	-0,732951015	-1,804071478	-0,732951015
Flex % peak	-0,090186598	0,030445123	-2,962267499	0,015900846	-0,159058252	-0,021314945	-0,159058252	-0,021314945

Figure C.9: Regression output from the regression with LHSP as its dependent variable and total thermal capacity and flex capacity as a percentage of peak demand as its dependent variables

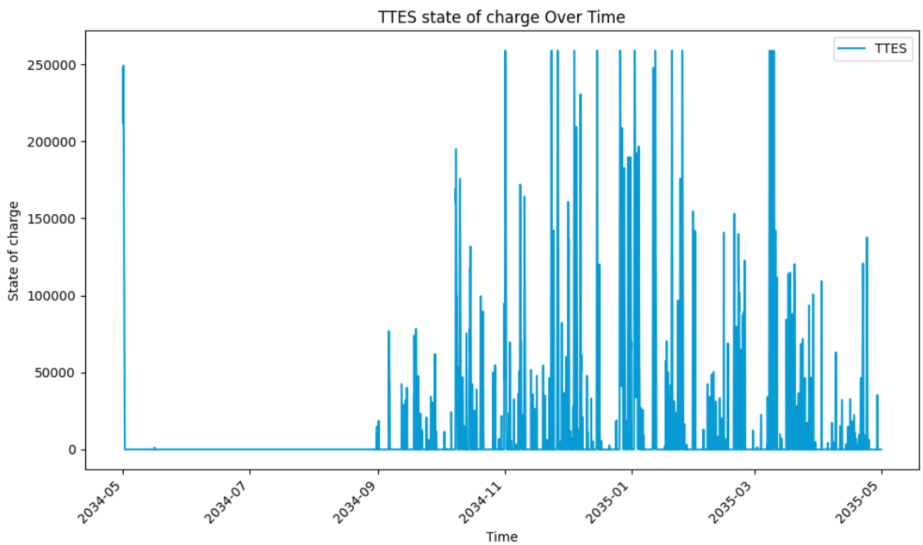

Figure C.10: The state of charge of the Tank Thermal Energy Storage (TTES) over time

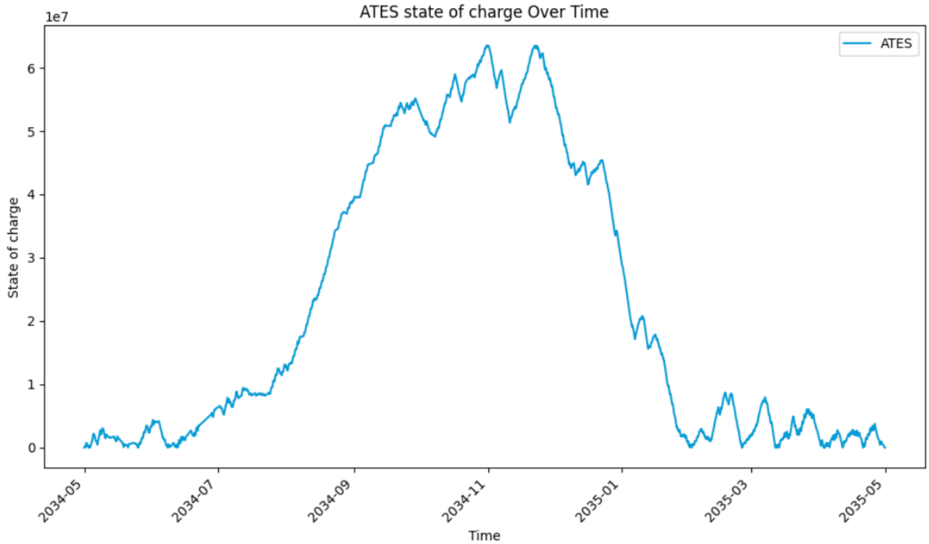

Figure C.11: The state of charge of the Aquifer Thermal Energy Storage (ATES) over time

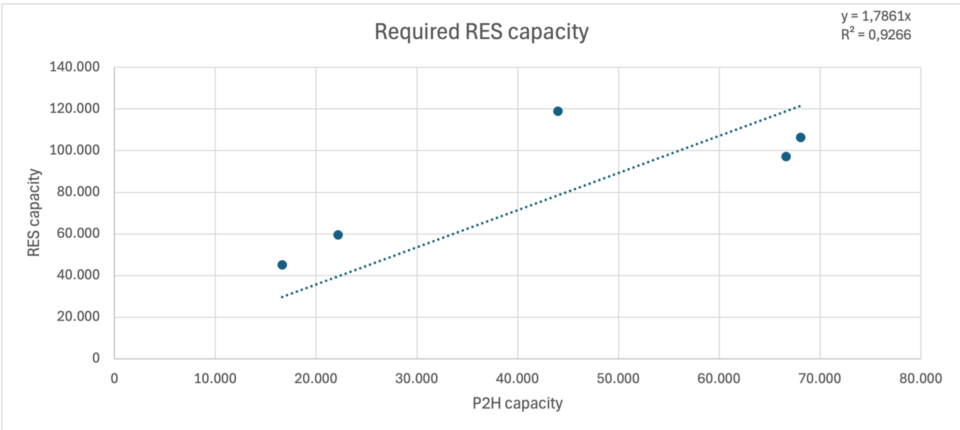

Figure C.12: A linear regression with required renewable energy sources (RES) capacity as its dependent variable and total power-to-heat (P2H) capacity as its independent variable for the bifurcation and removal scenarios.

C

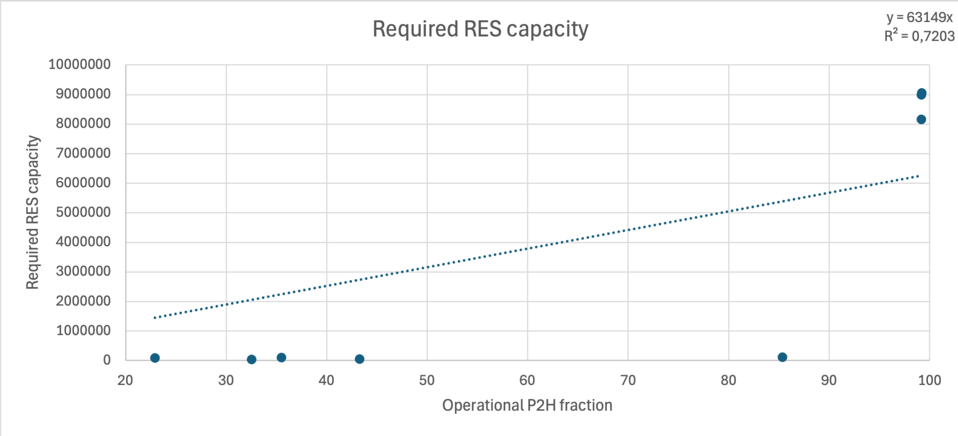

Figure C.13: A linear regression with required renewable energy sources (RES) capacity as its dependent variable and the operational P2H fraction as its independent variable for across all scenarios.

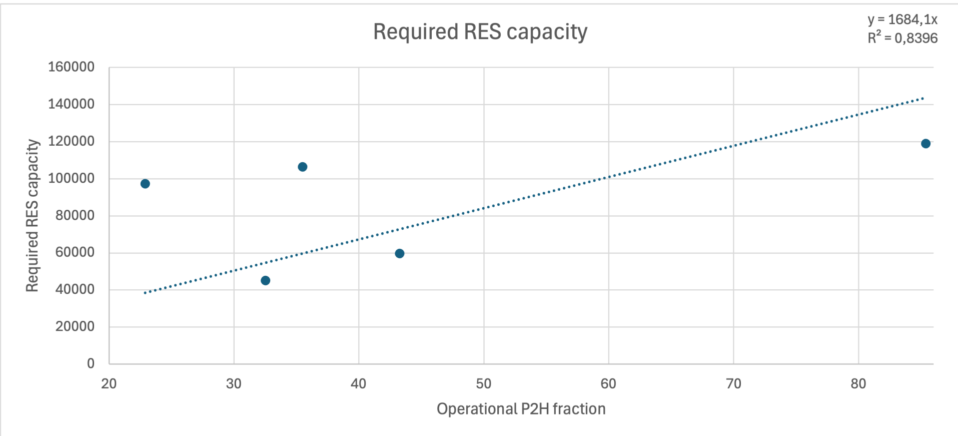

Figure C.14: A partial linear regression with required renewable energy sources (RES) capacity as its dependent variable and the operational P2H fraction (up to 85%) as its independent variable.

C

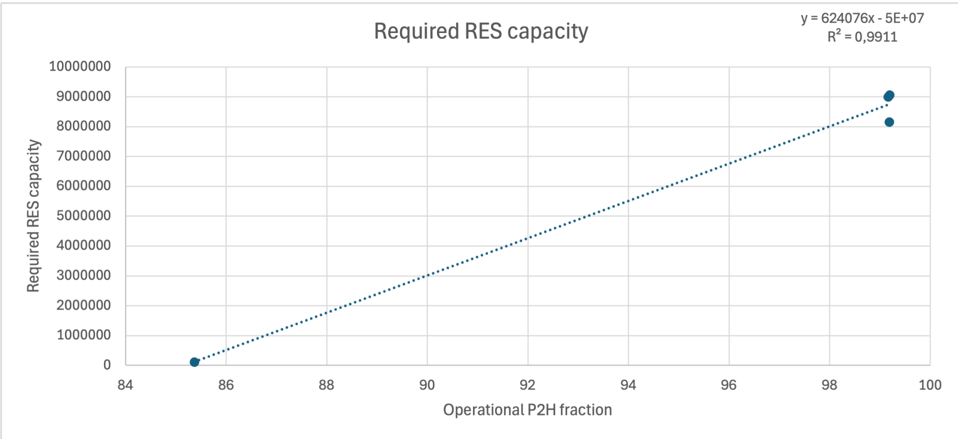

Figure C.15: A partial linear regression with required renewable energy sources (RES) capacity as its dependent variable and the operational P2H fraction (From 85% up to 100%) as its independent variable.

D

Appendix D: Validation

When discussing validation of an optimization model, demonstrating that the results align with logical and expected trends is a key step in building confidence in the model. In this case, two regressions were performed to analyze the relationships between the power-to-fuel price ratio and the installed capacities of power-to-heat (P2H) and fuel-to-heat (F2H) technologies (Appendix C.1 & C.3).

The first regression demonstrates that as power becomes more expensive relative to fuel, the optimization model results in less installed P2H capacity. Conversely, the second regression shows that as fuel becomes cheaper relative to power, the installed F2H capacity increases. These findings align with intuitive and theoretical expectations: when power prices rise compared to fuel, the economic incentive to rely on P2H technologies diminishes, while cheaper fuel prices make F2H technologies more attractive.

This alignment between the model's outputs and logical market behavior serves as evidence of model validity. By producing results that reflect realistic decision-making patterns in energy system design, the model demonstrates its ability to provide credible and consistent outcomes under varying input conditions. These relationships not only validate the model's internal logic but also enhance its credibility for supporting strategic decisions in energy system planning.

Furthermore, we can validate model behaviour through the first law of thermodynamics which states that energy can neither be created nor destroyed. Therefore the model must show identical energy inflows and outflows which is the case in the presented optimisation model (Figure D.1).

D

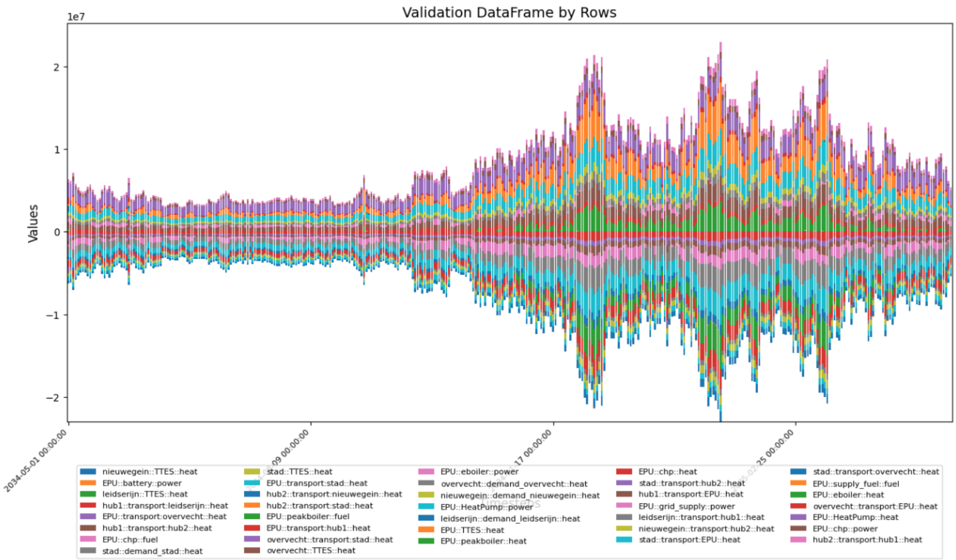

Figure D.1: Validation dataset illustrating equal energy inflows and outflows across all timesteps in the model output.

E

Appendix E: Modelling of system components

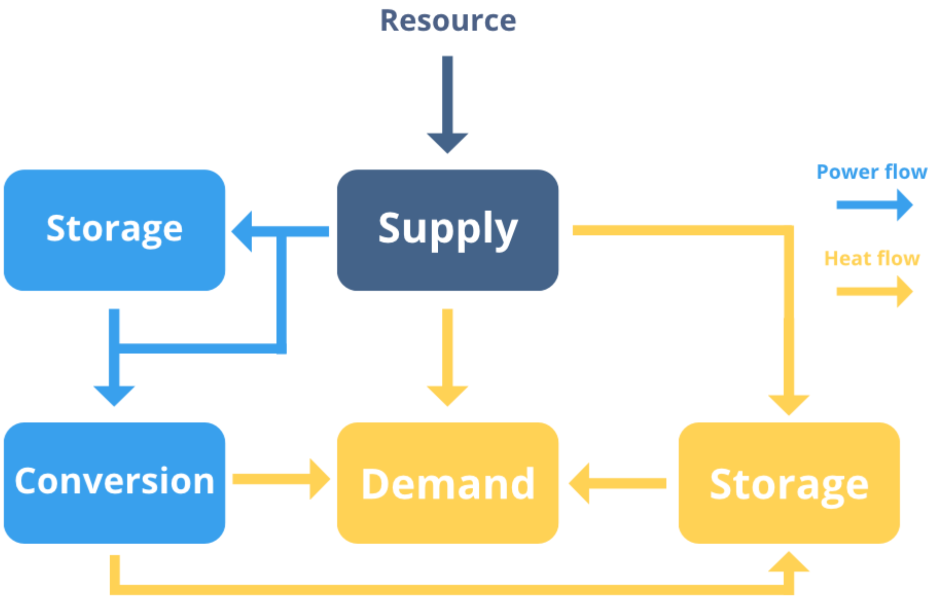

Figure E.1: A visual representation of energy flow in the optimization model: Blue blocks represent assets that use power as their input carrier, while orange blocks represent assets that use heat as their input carrier.

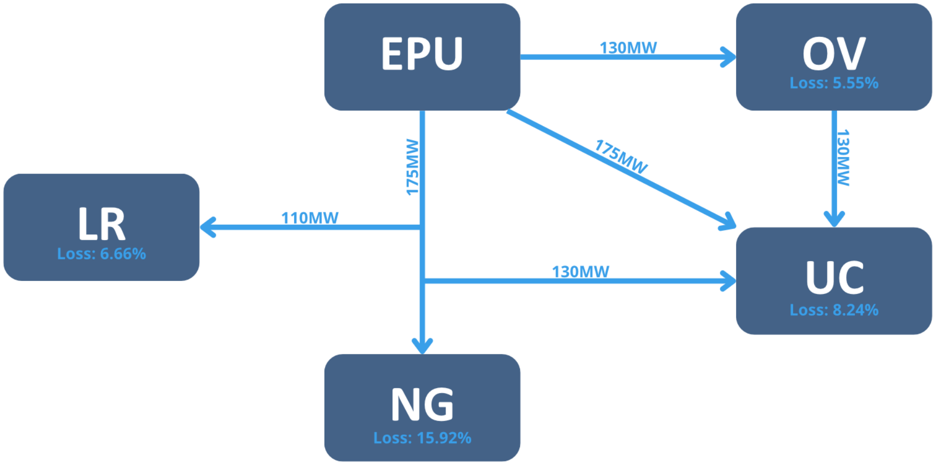

Figure E.2: The spatial configuration of the DHN in Utrecht, connecting EPU with the different districts: Nieuwegein (NG), Leidsche Rijn (LR), Overvecht (OV), and Utrecht city (UC). For each district, the total thermal losses during transport along the shortest route are presented.