# Identifying weather robust high-performing energy system configurations to aid decision-making

A case of the North Sea energy system

Philip T. de Jong

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**Studentnumber:** 4933427

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# A case of the North Sea energy system

by

Philip T. de Jong

in partial fulfilment of the requirements for the degree of

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**Thesis committee:**

Dr. S.J. (Stefan) Pfenninger (Chair)
Dr. P.W.G. (Pieter) Bots (2nd supervisor)
Dr. F. (Francesco) Lombardi (advisor)



TU Delft

# Preface

The past semester has marked the beginning of the last part of my education at the TU Delft. During this semester I have indulged myself in the world of energy system modelling to provide impact for decision-making. It has resulted in a thesis that aims to explore the technical realm of the North Sea energy system whilst keeping the real-world aspect of decision-making in mind. Exactly how I was educated during my studies, as a multi-disciplinary engineer. My efforts have thus been on creating a multi-faceted thesis to provide general insight.

The process of creating this thesis has been a challenging time and I have found myself having to deal with various barriers. However, overcoming these barriers has provided me with the most valuable lessons and the most fun eventually, for which I am very grateful. I could not have learned these lessons without the great support I have received from my supervisors. I want to thank Stefan for giving me the chance to work on this wonderful project and discover Calliope. I want to thank Pieter for being involved and passionate in guiding me and the project towards a better outcome, something I have always experienced in my encounters with you through five years of being a TPM student. Lastly, I am very grateful for the supervision I have received from Francesco. You have persistently helped me with all facets of this thesis and were always very approachable to guide me to not only a better result but also a better understanding.

Privately I owe a lot of gratitude to my dear girlfriend Sybel for all the great motivation and resilience I have received during the whole thesis process. I also want to thank my parents and brother Alex for providing their guidance and constant support. Lastly, thank you to my roommate Twan, with who I have gone through the thesis process in parallel which always provided a great sparring partner.

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# Summary

The ever-rising greenhouse gas emissions move the European Union to transition towards a future decarbonized energy system. To achieve this, the future energy system will mainly comprise variable renewable energy generation sources. Energy production from these sources is susceptible to weather fluctuations. Uncertainty of future weather scenarios translates into energy system models that help decision-makers to design the future renewable energy system. Energy system models often use a single weather year to simulate weather behaviour. Thus, many energy system models fail to take weather fluctuations between various years into account. Identifying energy system designs that are robust to weather fluctuations, i.e. systems that are able to suffice demand regardless of the weather circumstances, is therefore key.

The research described in this thesis has aimed to develop and test a method to give insight to decision-makers into the composition of robust and efficient energy systems, given weather uncertainty. To achieve this, the SPORES methodology has been used and extended to identify energy system configurations that are both robust and efficient. For this, a decision option space for decision-makers has been created that has been diversified based on renewable energy generation and storage technologies. To test the developed method, the North Sea region has been used as a case, as this is the region thought by policy to have great potential to house renewable generation sources in Europe.

The method developed in this research systematically covers the decision option space over three weather scenarios (worst, typical and best). From these decision spaces, configurations that meet demand with installed capacities that exist across the whole weather options space have been selected as robust. Clustering was used to identify types of energy system configurations, having commonalities in the installed generation capacities. Energy efficiency has been identified as key for measuring energy system performance. This research, therefore, takes curtailment and energy system yield into account to quantify efficiency. Using a Pareto analysis, both robust and efficiency-wise high-performing energy system configurations were identified as most promising for decision-makers.

Figure 1 visualizes the main results. The no-regret decisions, visualized by the SPORE-core, are minimum capacities required across the whole decision space. Results showed that robust energy systems are typically comprised of balanced configurations, meaning that solar PV and wind power both have the largest capacity of energy generation sources. The balanced configurations also contain high transmission capacities and typically no storage capacities indicating energy is distributed rather than stored. The robust and efficient configurations need additional capacity investments on top of the no-regret decisions. Especially solar PV needs a large increase in capacity when robustness and efficiency are required. Combined heat and power from biofuels and electrolysis capacity are also key to robust and efficient configurations. Additional results showed that the majority of robust and efficient configurations utilised more offshore than onshore wind capacity.

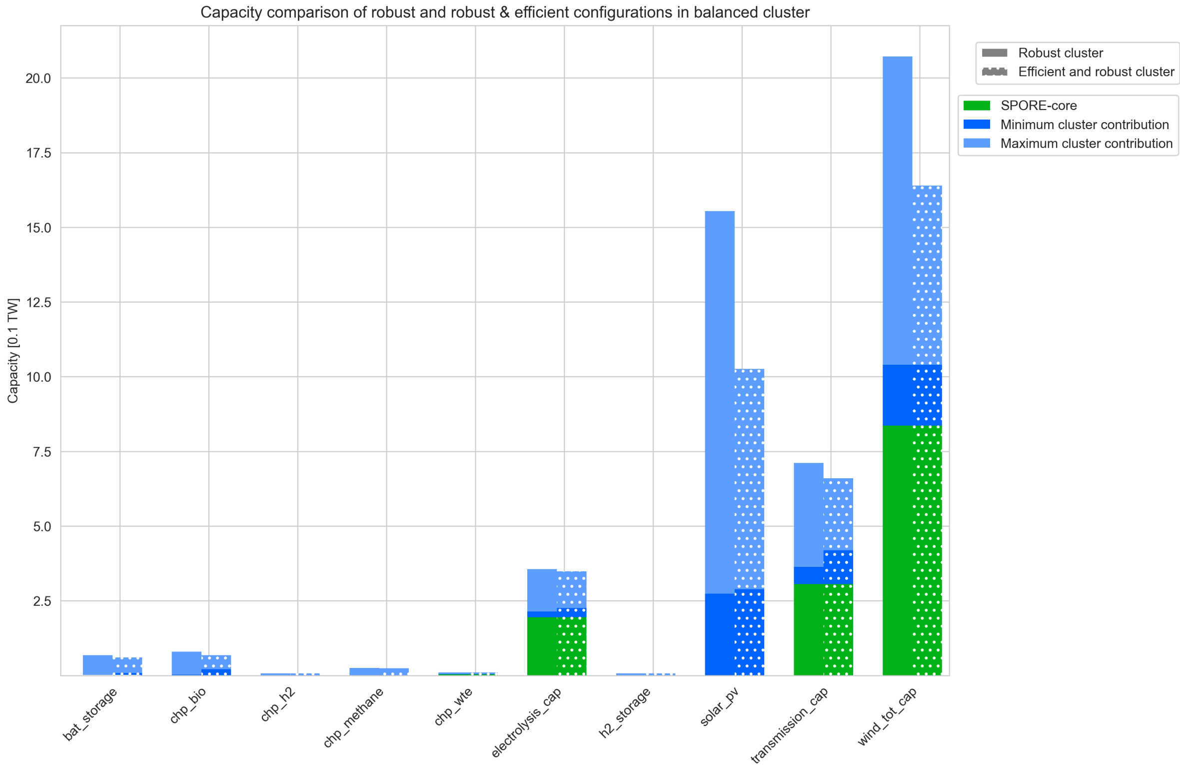


Figure 1: Bar chart showing the minimum capacity required per technology (SPORE-core, no-regret decisions). The left bars show the minimum and maximum capacity values of the robust cluster per technology. The right bars show the minimum and maximum values of the high-performing configurations in the robust balanced cluster per technology. A dark blue bar means there is additional capacity needed on top of the no-regret decisions.

The findings of this research are based on a case of the North Sea energy system with a high level of aggregation and are thus of limited use for precise designs of the North Sea energy system. The method created in this study can be adapted to contain more detail and offers space for researchers to include their own performance indicators. However, this research already used significant computational efforts, so adding more resolution and detail will mean the computational process can be restricting. Future research should focus on using the developed method to select promising and robust energy system configurations with higher levels of detail and conduct further weather scenario analyses on the selected configuration.

# Acronyms

**CCS** carbon capture and storage.

**CHP** Combined Heat and Power.

**EH** Energy Hub.

**ESM** Energy System Modelling.

**EU** European Union.

**GHG** Greenhouse gas.

**MGA** Modelling to Generate Alternatives.

**NSEC** North Sea Energy Cooperation.

**NSR** North Sea region.

**REG** renewable energy generation.

**SPORES** Spatially Explicit Practically Optimal Results.

**WTE** Waste to Energy.

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# 1 Introduction

Greenhouse gas (GHG) emissions are rising, the climate is changing and energy demand is at an all-time high (International Energy Agency, 2022c). Since 75% of Europes GHG emissions originate from the energy sector, Europe finds itself in a surge for a more green and sustainable energy system (European Commission, n.d.). This has led to the target of a minimum of 32% renewable energy installed by 2030 in the EU, as described in the Renewable Energy Directive (2009/28/EC), and to the aim of becoming carbon neutral in 2050. The North Sea region (NSR) bears great potential to accommodate renewable energy generation (REG) technologies. The REG technologies that are mainly used, solar PV and wind turbines, are characterised by weather dependence. Not only supply, but energy demand is also highly dictated by the weather, extreme cold periods cause a major heat demand and periods of low wind speeds and solar irradiation cause a decline in energy supply for example. A future European energy system, therefore, is influenced by weather patterns and the implemented REG technologies (Drake et al., 2019). With the weather-dependent character of current demand and renewables, the challenge remains for the EU on how to design a robust and renewable energy system.

Targeting a share of 32% renewable energy in the EU by 2030 and a carbon neutral energy system by 2050 means society needs to rapidly implement REG technologies. Currently, the EU has a renewable energy share of 22%, thus needing to increase by 10 percentage points. The NSR is considered to house a great share of the renewable energy production capacity for the whole of the EU (Cleijne et al., 2020). Looking at the North Sea Energy Cooperation (NSEC) countries, it becomes clear that only Denmark, Norway and Sweden have surpassed the goal of 32% renewable energy generation share (Eurostat, n.d.). Not a single NSR country is close to becoming climate neutral. Challenge, therefore, remains to utilise the potential of the NSR for REG technologies.

Becoming more renewable is a task across various sectors, not only does the electricity sector needs significant change, but also the transport, heat and building sector (European Commission, 2022). In 2020, the heating and cooling sector had a renewable share of 23.1% for the transport sector this share was substantially lower at 10%. The electricity sector has the highest share of REG technologies, with 37.5% of renewable energy in the EU (European Commission, 2022). Most REG technologies produce energy in the form of electricity, thus other sectors will increasingly need to use electricity to become renewable. The heat sector will largely need electric heat pumps and the transport sector will need an increased amount of electric vehicles. Therefore, for the future energy system renewable electricity production capacity must increase.

Decision-makers of the EU have the task to direct the designing of this future energy system. As Miller et al. (2015) show, decision-making on energy policy is multi-dimensional, consisting of technological, economic, social and political challenges. A single technical optimal design will not suffice the needs of decision-makers and restrict progress. To give decision-makers a broad scala of future energy system configurations, multiple models that depict the future energy system are being used (Fattahi et al., 2020). Energy System Modelling (ESM) proves a powerful tool to facilitate long-term strategies to design the future energy system (Fattahi et al., 2020; McPherson et al., 2023; Pfenninger et al., 2014). An effective tool to aid decision-makers by providing multiple energy system configurations is the Spatially Explicit Practically Optimal Results (SPORES) method proposed by Lombardi et al. (2022). This method gives a broad scala of diverse energy system configurations, all within 10% of the economic optimum. It provides decision-makers with a multitude of options to decide on the future of the energy system. Though uncertainty is still translated into the final configurations, the multitude of semi-optimal options provides a larger decision space for decision-makers as a base for an energy system design. However, the weather remains an uncertain factor with a high impact on energy system models (Fattahi et al., 2020), this includes the SPORES method.

Therefore, decision-makers are confronted with the impact of weather uncertainty on energy system models. Identifying robust energy systems could mitigate uncertainty. Mens et al. (2011) define robustness as: "...a system's ability to remain functioning under disturbances." For energy systems subject to weather impact this means that an energy system should suffice energy demand throughout varying weather scenarios. Since energy system modelling often uses a single historical weather year to model weather behaviour (Staffell & Pfenninger, 2018), insight into the impact of weather uncertainty on the energy system is limited. Additionally, because of large amounts of weather-dependent renewable energy in the future energy system, the efficiency of the system is hampered (Grube et al., 2018). Moreover, Villamor et al. (2020) show that renewable generation technologies such as wind (onshore and offshore) and solar PV positively correlate with curtailment. On top of that, Kanno and Ben-Haim (2011) show that system robustness is paired with system redundancy. Redundancy in turn leads to loss of efficiency, for example in the form of curtailment. Thus, the challenge remains to find robust and efficient energy system configurations given weather uncertainty.

Calliope is a ESM tool that is capable of modelling energy systems with high spatial and temporal resolution (Pfenninger & Pickering, 2018). The mentioned SPORES methodology is also implemented in Calliope, making it a tool suited to generate insight into energy systems for decision-makers. With Calliope, a sector-coupled model of the European energy system was made, called sector-coupled Euro-Calliope (Tröndle & Pickering, 2020). By excluding all the non-NSR countries from Euro-Calliope, the North Sea Calliope model was built. North Sea Calliope reflects each NSR country with one node, in which all energy sectors are present. North Sea Calliope has 9 historical weather years (from 2010 to 2018) that each can be used to run the model. With these weather years, optimizations can be run to simulate the configuration of the energy system with various optimization horizons. The North Sea Calliope model allows the simulation of energy system configurations until the year 2050.

Given the challenges described, the aim of this research is to develop a method that uses the SPORES methodology to give insight to decision-makers into the composition of robust and efficient energy system configuration given weather uncertainty. To accomplish this, the research questions below have been constructed:

*What are robust and efficient energy system configurations throughout varying weather year decision spaces in the North Sea energy system?*

To structure the answering of the above research question, multiple sub-questions have been devised.

1. How can a multitude of robust energy system configurations be identified to aid decision-making given weather uncertainty?
2. What composition of generation technologies constitutes a robust energy system?
3. What are the most efficient energy system configurations given robustness?

In order to answer the research questions, a model study with an up-front stakeholder analysis has been conducted. The stakeholder analysis uses academic and grey (policy) literature to form an understanding of the current state of the North Sea energy system decision-making and the problems that different stakeholders and countries face. Subsequently, a modelling study has been conducted to generate insight into robust and efficient energy system configurations. This modelling study has used North Sea Calliope as the Energy System Modelling (ESM) tool and the SPORES methodology. SPORES have been used to generate multiple energy system configurations with a large diversity in energy generation technologies. This diversity makes up the decision space for this research to give insight into multiple possible configurations for decision-making. After this, configurations that are robust to weather impact were identified in the decision space. Analyses have been conducted to explicate the makeup of robust configurations when looking at main generation technologies. Parallel to this, an effort has been made to identify efficient configurations. Lastly, this research identified which robust configurations are also efficient, to provide insight into the method that decision-makers can use to find robust and efficient configurations.

This research is divided into five chapters. In chapter 2, a concise literature review has been conducted. In chapter 3 the methods of the modelling study have been discussed. Chapter 4 has discussed the results of the modelling study. Finally, in chapter 5, a reflection on the results and limitations of this research has been made and provides recommendations for future research.

# 2

# Background

## 2.1. Literature study

The future energy system is highly influenced by weather fluctuations. This is mainly caused by the large share of intermittent renewables in the future energy system (Meenal et al., 2022; Pfenninger & Staffell, 2016; Staffell & Pfenninger, 2016). Especially wind turbines and solar PV call for balancing measures, because of their high roll-out in the energy system and electricity market. Moreover, future heat demand will partly be electrified, meaning that additional demand is created for intermittent electricity generation sources in the future (Sánchez Diéguez et al., 2021). Cold, dark and windless days, so-called Dunkelflauten, will stress a renewable energy system due to high (heat) demand and low supply (Otero et al., 2022). Additionally, Sakellaris et al. (2018) shows that the current energy system is vastly interconnected. Therefore, weather fluctuations in one part of the energy system will influence the energy supply in other parts. When the energy system keeps evolving towards more weather dependence, control of generation and demand will increasingly be lost (Bloomfield et al., 2016; Zavala et al., 2010). Moreover, conventional fossil base-load covering power plants will be phased out by more weather-dependent renewables which makes it harder to draw a predictable generation scheme.

Decision-makers, or policy-makers, of the EU are tasked with making crucial decisions on the future design of the European energy system. The impact of weather uncertainty on this design is therefore directly translated into decision-making (Mavromatidis et al., 2018). Currently, decision-makers are searching for flexibility means that mitigate the uncertain and intermittent nature of renewables. Storage is pointed to as a flexibility mean that will fulfil a significant role in the future energy system to mitigate energy fluctuations (Pupo-Roncallo et al., 2020). However, storage is dependent on the generation source which is supplying energy to the storage, meaning weather fluctuations are partly translated into flexibility means. Moreover, Yalew et al. (2020) show that weather impacts on a local scale are even more unpredictable. Given the interconnectedness between energy supplying and using sectors, the effects that fluctuating weather years will have are hard to explicate for decision-makers. Decision-makers are in need of tools that give insight into the design of the future energy system and its uncertainties.

The need decision-makers have for a long-term strategy for the design of the future energy system has brought about Energy System Modelling (ESM) (Pfenninger et al., 2018; Sakellaris et al., 2018). According to Pfenninger et al. (2014) energy system models can be divided into “energy systems optimization models, energy systems simulation models, power systems and electricity market models, and qualitative and mixed-methods scenarios”. Pfenninger et al. (2014) further explicate an important distinction in ESM, namely the presence of predictive models in the form of forecasting/simulation models, and the normative energy system models which are less focused on forecasting future energy scenarios. More precisely, Bazmi and Zahedi (2011) show that optimization models have found increased use in allocation problems and design engineering, for example, the allocation of power demand and supply. Moreover, optimization models have been found to be critical in analyzing environmental, and energy, policy (J. DeCarolis et al., 2017). Using optimization models in ESM requires a detailed approach. Especially, making a thorough spatiotemporal demarcation is key, where models with a high share of REG sources ask for an elevated spatiotemporal resolution (J. DeCarolis et al., 2017). Energy System Modelling used to depict the future for decision-making will make use of high levels of renewables and a multitude of energy carriers and optimizes generation capacities costs. Fodstad et al. (2022) show that most multi-carrier energy system models face the trade-off of the short-term matching mechanisms of demand and supply and the long-term choices of capacity expansion. Models that aim to provide a detailed long-term perspective of capacity planning often lack short-term temporal resolution. To overcome this problem, ESM can make use of an Energy Hub (EH). Mohammadi et al. (2017) define EHs as: "...the place where the production, conversion, storage and consumption of different energy carriers takes place...". An EH does however not solve the problem of uncertainty of future weather conditions being translated into ESM.

Energy system models often contain large shares of renewables with their future behaviour often being based on just a single historic weather years (Jahns et al., 2023). As Staffell and Pfenninger (2018) also show, ESM mostly use short time spans to model future weather behaviour based on historical weather data. The energy system of the future needs to be robust to weather fluctuations, so ESM will be used to identify robust configuration options. A study by Gabrielli et al. (2019) uses a single, typical weather year to chase a robust energy system configuration. Gabrielli et al. (2019) accept hourly demand not being fully met as robust, whilst a scenario where hourly demand would fully be met by supply would require an abundance of renewable capacity. Perera et al. (2020) therefore took a range of weather scenarios into account but did note that the computational efforts quickly rise when including more weather scenarios in ESM. Quitoras et al. (2021) have taken robustness into account but saw the outcome of their multi-objective optimization model quickly rise when the most-promising configurations were regarded. This implies that system costs and redundancy of capacity rise when modelling for robustness.

Additionally, given the uncertainty of model factors such as weather, chasing a single optimal solution with ESM can be "misleading" (J. F. DeCarolis et al., 2016). The focus should therefore be on generating multiple alternative configurations to generate more valuable insight (J. F. DeCarolis et al., 2016). One method of ESM to systematically explore the decision space is Modelling to Generate Alternatives (MGA). More specifically, MGA generates very different energy system configurations so that the decision space is properly mapped (J. F. DeCarolis et al., 2016). Decision-makers particularly benefit from modelling near-optimal solutions, because decision-makers often do not choose the cost-optimal solution due to other political, social or environmental factors (Prina et al., 2023). Lombardi et al. (2020) even state that, due to the uncertainty, future energy system configurations within 10% of the economic optimum are hard to distinguish from the optimal solution for decision-makers.

A method of implementing MGA is the Spatially Explicit Practically Optimal Results (SPORES) methodology. SPORES differ spatial deployment of technology in the energy system model. SPORES is currently being deployed in the Calliope energy system model (Lombardi et al., 2020). SPORES are, however, different from usual MGA methods. Where MGA tries to make as different as possible configurations based on assigning penalties on energy technology capacities, SPORES takes the spatial deployment of various energy technologies into account (Lombardi et al., 2022). An example from Lombardi et al. (2022) states that MGA will penalise wind generation in general if it is highly used in the cost-optimal solution and SPORES will only penalise based on the spatial deployment of the technology, so per location, a separate penalty exists. With SPORES a more thorough representation of the possible decision space can be made compared to regular MGA methods. Figure 2.1 provides an overview of the SPORES workflow.

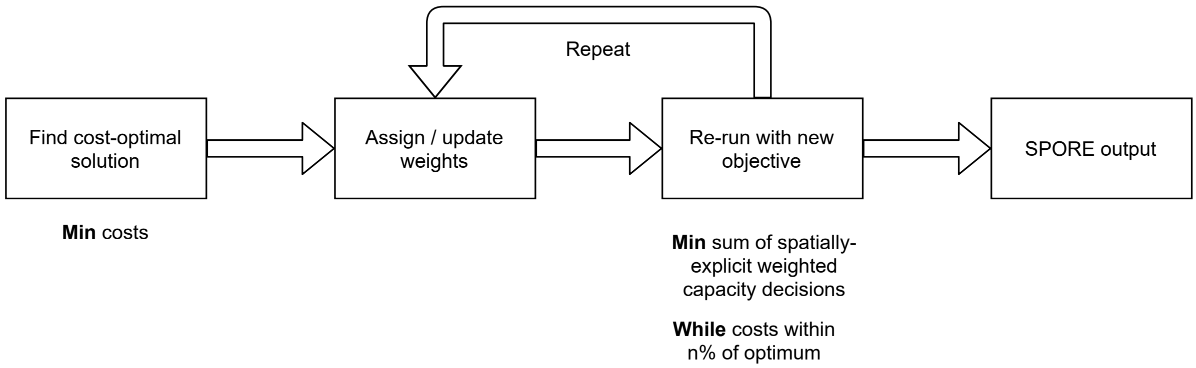


Figure 2.1: SPORES workflow adapted form Lombardi et al. (2022)

# 3 Methods

This chapter describes the methods that have been used to identify robust and efficient energy system configurations. Figure 3.1 shows the methodological steps that have been taken in this research. Each of the steps will be discussed in the sections below, where the numbers attached to the processes in the figure correlate to the order in which each process will be discussed. The first two sections will explicate the use of Calliope and the measures which will be used for analyses. After, the methods as described in the figure will be explained.

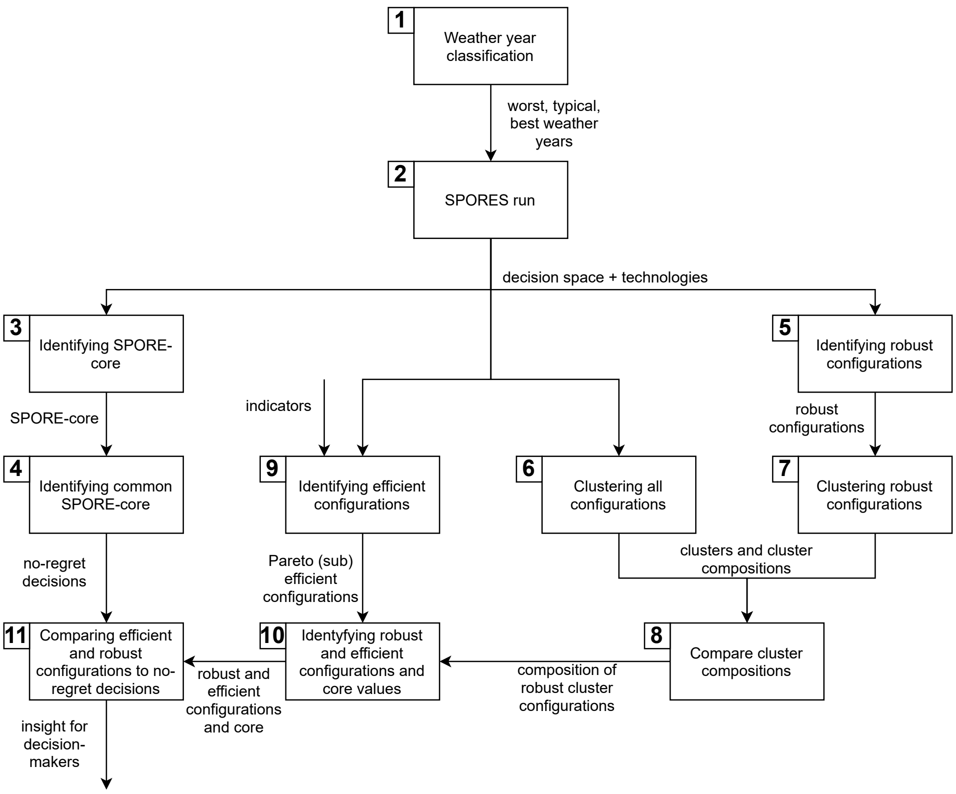


Figure 3.1: Flow diagram of the research methods. Each process number represents the order in which they are discussed in this chapter.

## 3.1. Calliope, inputs and SPORES

In order to systematically explore decision spaces created by various weather scenarios, this research used the ESM tool Calliope. Calliope is capable of modelling energy system models with high spatial and temporal resolution. Calliope uses data on energy demand, energy generation capacities, and costs per location (Pfenninger & Pickering, 2018). Scenarios are used to override certain parameters to suit the specific case. These inputs are assembled into an energy system model. This is then optimized for costs, to generate the cost-optimal solution that meets all given demands with the technology constraints. The solver used in this research to solve the energy system model is a third-party solver called Gurobi (Gurobi Optimization LLC, 2023). The output is a model file from which the energy system configuration, capacities, costs, and production can be extracted. The visual representation can be seen in figure 3.2.

Specifically, this modelling research used the already created sub-set of the fully sector-coupled European Calliope model, named North Sea Calliope. Countries modelled in the North Sea Calliope are Belgium, Denmark, France, Germany, Great Britain, Ireland, Luxembourg, the Netherlands, Norway, and Sweden (the NSR countries). Each country is represented in the model by a node in which demand and supply are aggregated. The transmission lines between the nodes consist of DC subsea transmission, DC underground transmission, or AC overhead lines transmission, see figure 3.3.

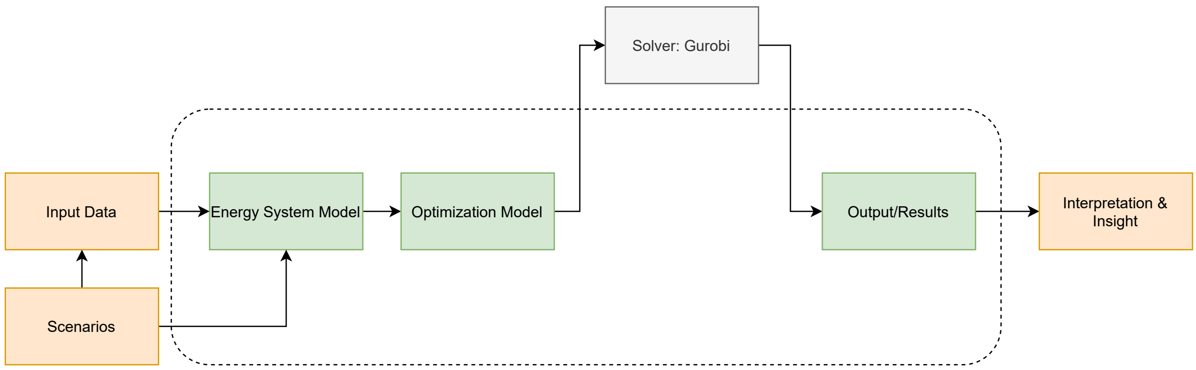


Figure 3.2: Conceptual representation of Calliope, adapted from Pontes Luz and Amaro E Silva (2021)

Calliope creates a linear optimization problem where supply needs to match demand. The decision space for the model is the n-dimensional space (n being the number of decision variables), where the optimal solution lies within. Decision variables make up the decision space. Seventeen main decision variables are contained in the North Sea Calliope model. Each main decision variable has dimensions, such as timesteps and/or locations for example. Multiplying all the main decision variables by every one of the dimensions gives the total number of decision variables that span the decision space (Calliope contributers, n.d.). Since the North Sea Calliope contains ten countries and every hour of the year is optimized, multiple thousands of decision variables make up the decision space. In order to effectively explore the relevant decision space, relevant technologies and indicators for further analysis need to be used.

The SPORES algorithm is being used with the North Sea Calliope model for this research. Using the methodology that can be seen in appendix A.1, SPORES are created. A single SPORE represents a fully run energy system model in North Sea Calliope, where the total system costs are within a chosen percentage of the total system costs of the optimal solution. In this research, the total system costs are able to deviate a maximum of 10% from the total system costs of the optimal solution. A single SPORE will yield a fully calculated model of an energy system. A SPORE can hence also be referred to as an energy system configuration or simply configuration.

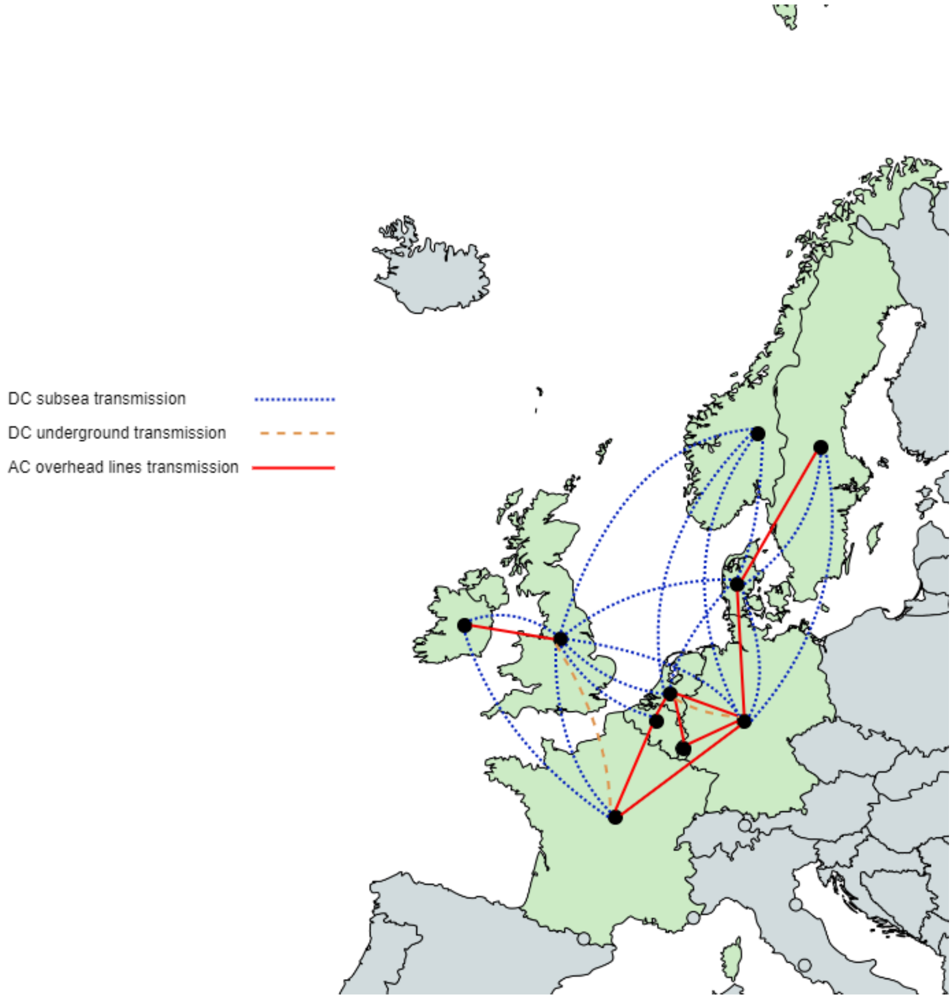


Figure 3.3: Transmission and node map of North Sea Calliope

## 3.2. Technologies and indicators

Due to the large dimensional decision spaces generated in North Sea Calliope, a set of technologies to systematically analyse the model outcomes were chosen. With these technologies, the composition of energy systems can be explicated, which was ultimately used to answer the main research question. The technologies are model outcomes, which show the capacities of said technology in the energy system configuration. In order to holistically explore the composition of configurations, all main supply technologies present in North Sea Calliope are to be regarded. Moreover, the country and stakeholder synthesis performed in appendix A shows that a few main generation technologies are controversial or recommended for future use. Especially wind power is controversial since various stakeholder groups see their income threatened by offshore North Sea wind deployment. The stakeholder overview also shows that countries are recommended to research hydrogen as a future energy carrier and storage medium. These technologies are among the main generation technologies and thus are taken into account. This research did not assign a weight for interpretation to these technologies. Rather it aimed to provide insight into which decision-makers can incorporate their own out-of-model factors and key points. Table 3.1 gives an overview of the main supply technologies from the North Sea Calliope model, with short names for the technologies. These technologies were used for the analyses of the generated decision spaces.

When looking at capacities, a SPORE (or configuration) as constructed by Calliope, in this research, was represented by a pandas data frame in Python. Each country was represented by a row in this data

| Technology | Short name |
|---|---|
| Installed wind capacity (offshore + onshore) | wind_tot_cap |
| Installed transmission capacity | transmission_cap |
| Installed electrolysis (hydrogen) capacity | electrolysis_cap |
| Installed battery storage capacity | bat_storage |
| Installed hydrogen storage capacity | h2_storage |
| Installed solar PV capacity (farm + roof) | solar_pv |
| Installed chp hydrogen capacity | chp_h2 |
| Installed chp from methane capacity | chp_methane |
| Installed chp from biofuels capacity | chp_bio |
| Installed chp from waste to energy capacity | chp_wte |

Table 3.1: technologies for energy system configuration analysis

frame, whilst the columns represent all technologies present in the model. Since the whole of the North Sea region has been regarded and whole energy system configurations have been compared with each other, individual country data are aggregated to the system level. Therefore, for each technology, the technology value of an energy system configuration (SPORE) is the summed value over all countries. For example, the capacity value $C$ of solar_pv for a single SPORE is calculated as the sum over all regions (countries) of solar farm plus the sum over all regions of solar roof: $C_{solar\_PV} = \sum_r C_{r,solar\,farm} + C_{r,solar\,roof}$ for all regions (countries) $r$. In the same manner, production has been extracted from Calliope, only the capacity value was then replaced with production per technology per country.

In order to identify efficient energy system configurations, for answering the main research question and sub-question 3, the performance of these configurations has been tested. Indicators have been identified according to a stakeholder and country analysis, see appendix A. A main finding was that the efficiency of the energy systems ought to be on the agenda of various member states. Many indicators can be chosen to test for efficiency. This research has used total system yield and total system curtailment to demonstrate the method of finding efficient configurations. For yield, it has to be clear how much capacity is installed per technology and how much energy is produced. In equation 3.1 the total system yield is calculated. Since the system has been aggregated, the yield will be given as the mean yield over all the technologies. Second, the curtailment of an energy system has been calculated by multiplying the installed capacity with the capacity factor, to get the possible produced energy, and from that the actual produced energy delivered to the grid is subtracted, as seen in equation 3.2. Since we want a higher curtailment score to imply better performance, 1 is divided by the total system curtailment. In both equations, the capacity is multiplied with all hours of the simulated year, 8760 hours, to convert all units to energy instead of capacity.

$$Yield[\%] = \frac{\sum_i \frac{capacity_i \cdot 8760}{production_i}}{n} \quad for\ technologies\ i\ where\ n = number\ of\ technologies \tag{3.1}$$

$$CurtailmentScore[1/0.1TW] = \frac{1}{\sum_i capacity_i \cdot Cf \cdot 8760 - production_i} \tag{3.2}$$
$$for\ technologies\ i$$

## 3.3. Weather year classification

Identifying robust energy system configuration means that first weather scenarios that cover the whole available weather scenario space were identified. This is the first step in developing a method to identify robust and efficient energy system configurations, see figure 3.1. In order to construct weather scenarios, the 9 weather years of the North Sea Calliope model have been classified. Since the North Sea Calliope model, especially the SPORES algorithm used with North Sea Calliope, has high computational demands, a subset of weather years that best represent the whole weather years set was identified to efficiently use computing time[1]. This has led to the identification of the worst, typical and best weather years so that the extreme scenarios plus a typical scenario are covered. Since Calliope optimizes based on costs, the model configuration that yielded the highest overall system costs is the worst weather year. This configuration namely had to invest the most money to provide sufficient technology capacities to mitigate weather periods where renewable generation is low and demand is high. The typical weather year has been pictured as a weather year with median total system costs since this weather year appears the most. The best weather year was identified by the lowest overall system costs since this configuration needs the least money to invest in technologies. To make a classification, first, all 9 historical weather years (2010 to 2018) have been optimized with the North Sea Calliope model.

A resolution of one hour for the model was used to get the most accurate picture of the costs necessary for the system to meet demand given the weather year. A visualisation of total system costs per weather year is made, also showing the median. After that, the composition of technologies of the three selected weather years has been visualized. This was done to gain insight into the behaviour of the cost-optimal solution and what amount of capacity has been contained in good, typical and worst weather years.

## 3.4. Decision space with SPORES methodology

The decision spaces of the classified weather years have been constructed to allow the search for robust energy system configurations, step 2 in the method development. Since it was not known beforehand what technological composition a robust energy system configuration had, this research has strived to create diverse decision spaces to explore the whole realm of possible configurations. First, the use of SPORES to achieve diverse decision spaces is explained, after the make-up of the decision spaces is explicated.

### 3.4.1. SPORES run configurations

To systematically generate diverse energy system configurations, the SPORES algorithms, as described in appendix A.1 has been used. A batch of 20 'regular' SPORES was created with the evolving average algorithm. This batch did not minimize or maximize a single technology, rather it used the cost-optimal solution to base system diversity on. Additionally, to ensure maximum diversity of decision options has been generated, the main technologies found in table 3.2 have been maximized and minimized. This test provided insight into alternative ways the energy system can be made emission-free if a technology only has very low (excluded) or very high (maximized) capacity deployment. For each of the technologies described in table 3.2 10 SPORES have been run in exclusion (minimization) mode and 10 SPORES have been run in maximization mode. The exclusion mode gave the respective technology a high penalty in the first SPORE configuration. This penalty meant the technology has been seen as very costly by the model and other technologies were favoured since the algorithm optimized based on costs. In each of the following SPORES, the weight of this technology relatively decreases since other technologies gain more penalty. Therefore, in the first SPORE, this technology was (almost, the feasibility of the model is ensured) fully excluded and in the tenth SPORE the penalty of this technology was relatively lower compared to the penalty of other technologies. For the maximization mode, the first SPORE had a very high negative penalty for a certain technology since the models were all minimized for costs, a large negative number was equivalent to maximizing. In each of the following SPORES, similar to minimizing, the penalties of the remaining technologies are made smaller so that the relative weight of the negative penalty decreases in each following SPORE.

The table above shows the names of all the exclusion and maximization configurations. Per configura-

[1]This research uses the Delft High Performance Computing Centre, efficient use of this cluster is a prerequisite

| | Maximize | Exclude |
|---|---|---|
| **Battery** | max_bat | min_bat |
| **Biofuels** | max_bio | min_bio |
| **Hydrogen** | max_p2g | min_p2g |
| **Open field PV** | max_pvfarm | min_pvfarm |
| **Rooftop PV** | max_pvroof | min_pvroof |
| **Transmission** | max_trn | min_trn |
| **Wind offshore** | max_windoff | min_windoff |
| **Wind onshore** | max_windon | min_windon |
| **Wind combined** | max_wind | min_wind |

Table 3.2: Configuration of the children SPORES technologies

tion, 10 SPORES have been run, thus this totals $18 \cdot 10 = 180$ SPORES. As said, 20 original SPORES have also been run making the total SPORES 200. These total configurations have been run using the three classified weather years (worst, typical and best). Since only one weather year can serve as input in North Sea Calliope, the total amount of SPORES that was created is $3 \cdot 200 = 600$. With these SPORES an overview of the decision space has been made per weather year.

### 3.4.2. Decision space

After all the SPORES have been run, the decision spaces for all three selected weather years were visualized. The decision spaces give insight to decision-makers about the possible configurations of the future energy system. Later, when robust configurations were identified from the decision space, it became clear which areas of the decision space constitute robust configurations. Since this research used 10 technologies to analyze energy system configurations and 10 dimensions are not interpretable in a single visualization or table, the dimensions have been split. This was done by grouping the decision spaces into three main subjects.

1. Main renewable generation and transmission: this includes installed wind capacity, solar PV capacity and transmission capacity
2. Storage techs, this includes installed battery storage capacity, hydrogen storage capacity and electrolysis capacity
3. Combined Heat and Power (CHP) technologies, this includes installed CHP methane capacity, CHP biofuel capacity, CHP Waste to Energy (WTE) capacity and CHP hydrogen capacity

## 3.5. Finding the SPORE-core

Identifying the SPORE-core and common SPORE-core has been done to gain insight into the capacity that needs to be installed to constitute a robust energy system, step 3 and 4 in the method development.

### 3.5.1. SPORE-core per weather year

Before robust energy system configurations were identified, the “SPORE-core” has been found. This core namely represents the minimum required installed capacity of each technology across the decision space of a weather scenario. Later, these cores were used to identify the minimum required capacity across all weather scenarios. From the decision spaces and descriptive statistics described in section 3.4 the minimum capacity values per weather year and of all-weather years combined for each technology have become clear. These minimal values represent capacities that are no-regret decisions since this capacity is the minimum that is installed across all configurations in this research. For each technology, the minimum value has been found by finding the minimum of the SPORES capacity values for a technology, in mathematical formulation: $m_{i,y} = min(s_{i,y,1}, s_{i,y,2}, ..., s_{i,y,200})$ for technology $i$ and weather year $y$, where $m$ is the minimum value and $s$ is the SPORE system value. The SPORE-core for a weather year $Sc_y$ was then formulated as the collection of minimum values of all technologies, formulated as: $Sc_y = \{m_{i,y}\}$ for all technologies $i$ and weather year $y$.

### 3.5.2. Common SPORE-core

To be able to give insight into what capacities are a minimum requirement regardless of weather, the common SPORE-core has been identified. This core will later be used to make clear what additional capacities are needed when robustness is a prerequisite. The common SPORE-core comprises the minimum core values of all technologies for all three weather scenarios. Thus, for a single technology, the common core value is the minimum of the three weather scenarios' core values for that technology. This minimum of the minima is namely the amount of capacity that is installed in every configuration regardless of the weather scenario. The common SPORE-core was found by first identifying the minimum of the minima capacity values for technology $i$ across all three weather years (worst, typical and best): $M_i = min(m_{i,worst}, m_{i,typical}, m_{i,best})$, where $M$ is the minimum of the minima capacity values of a technology $i$. After, the common SPORE-core is the collection of the minimum of the minimum capacity values across all technologies $i$, represented as: $CSc = \{M_i\}$.

## 3.6. Finding robust SPORES

When the common core is known, we know what the minimum required capacity is across all configurations regardless of the weather scenario, step 5 of the method development. A robust energy system configuration is a configuration that should sufficiently meet demand with the installed capacities of technologies regardless of the weather scenario. The minimum of a robust configuration can therefore not be lower than the highest minimum technology capacity value across all weather scenarios. If this condition is not met, there exist configurations with a higher minimum technology capacity, meaning there are weather conditions that require a different energy system configuration. Finding robust energy system configurations in the known decision space, from section 3.4, meant searching for configurations that have capacity values equal to or higher than the maximum minimum technology capacity values, denoted as $Mn_i$ for all technologies $i$. Additionally, a robust energy system configuration should be able to meet demand in all weather scenarios, i.e. the capacity values of the technologies of a robust configuration should be contained in the decision spaces of all-weather years. The decision spaces did not have a common maximum capacity value for all technologies. Therefore, robust configurations should not only be bottom limited by the maximum minimum capacities but also by a collection of maximum values that exists for each weather year. This collection simply comprises the minimum maximum technology capacity values of all technologies across all weather years, denoted as $Mx_i$ for all technologies $i$. Finding robust system configurations meant SPORES were identified that have values for all technologies that exist throughout all the weather years. Consequently, this yields a range of the decision spaces, from the maximum minimum capacities to the minimum maximum capacity values, where a configuration is robust $s = s_r$ if it lies within this range for all technologies. Figure 3.4 shows a conceptualisation of the robust range. Each vertical bar represents the capacity values for a specific technology for all configurations in the respective weather year. The range of robust configurations, as can be seen, has a value for every weather scenario across all technologies, ranging from the maximum minimum to the minimum maximum capacity values. Configurations that are in the range for each technology are classified as robust. Mathematically formulated, a robust configuration (SPORE) has been found as follows:

$$s = s_r \; if \; Mn_i \leq s_i \leq Mx_i \quad for \; technologies \; i \tag{3.3}$$

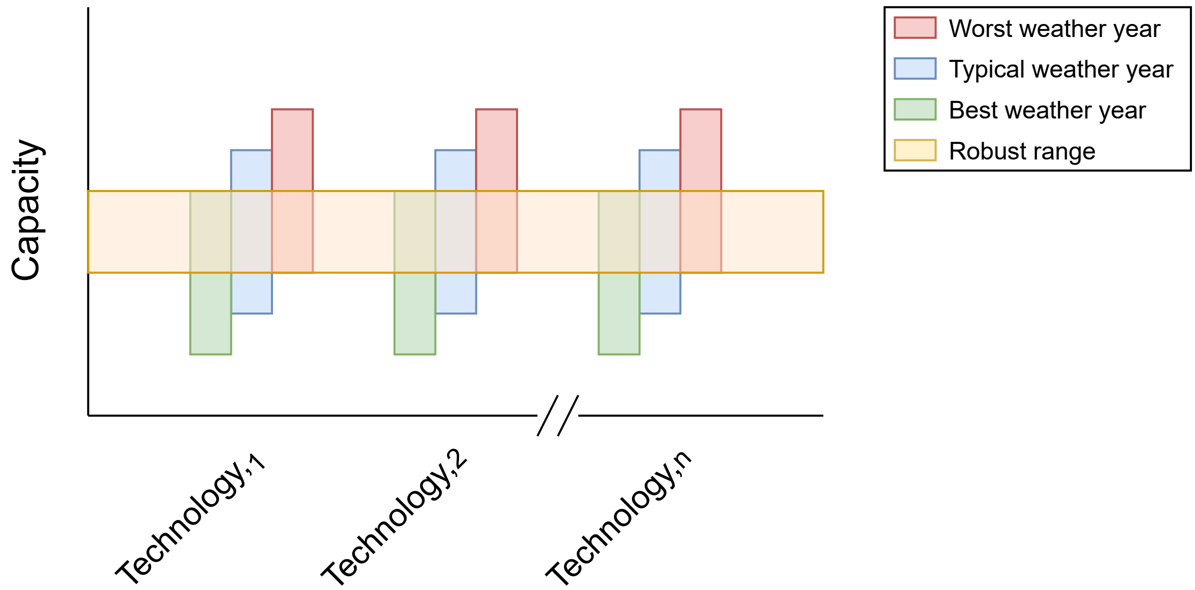


Figure 3.4: Range used to identify robust configurations. Each bar represents the capacity values of all configurations for the respective weather year. The robust range, in orange, is in between each maximum minimum value and minimum maximum value for a technology. Robust configurations have a capacity value for each technology that is within this range.

## 3.7. Clustering the SPORES

To gain insight into the composition of robust configurations compared to all configurations, for the answering of the main research question and sub-questions 1 and 2, the configurations contained in the decision spaces have been clustered (step 6, 7 and 8 of the method development). This means that similar configurations in the decision space have been grouped together to be able to generalise types of configurations. This meant a more simple interpretation of the results. Next, the robust configurations have been clustered.

### 3.7.1. Clustering all SPORES

All SPORES have been clustered based on their technology configurations, meaning that the outcomes of the technologies, as explained in section 3.2, have been used to base the cluster on. The clusters have been based on the Euclidean distance between the data points (data point = SPORE) in the decision space, which is the absolute distance between two data points. The distance between the farthest data points is then maximized to get clusters that have a large distance from each other in the decision space, meaning a large diversity in the configurations. In appendix B an explication of the chosen clustering algorithm can be found.

A hierarchical cluster method has been used since this does not assume that the amount of clusters to be made is known. Rather, a dendrogram has been created from which the number of clusters that best represent the configurations was arbitrarily determined. The dendrogram therefore first contained all the data points (SPORES) as the number of clusters, in this case, this contained all the 600 SPORES.

After the dendrogram is made, the cut-off point for the clusters has been chosen based on what the researcher deemed useful. In this case, if a branching in the dendrogram had a relatively large distance until the next branching, it was deemed useful. If the branching had a low distance until the next branching, it was deemed that two clusters were hard to distinguish from each other, here lies the cut-off point. Then, the number of branches at the cut-off point in the dendrogram was counted to determine the number of clusters. These clusters visualise the installed capacity of the technologies per configuration type.

### 3.7.2. Robust clusters

The cluster method described in the section above also served to identify robust clusters of SPORES. Once the robust SPORES had been identified, as described in section 3.6, the clustering algorithm was also run on this selection of SPORES. From this, a new dendrogram was created and clusters were identified as described above. Once the clusters had been identified, again the installed capacities of the technologies over the whole cluster have been visualized. With this, a qualitative interpretation has been made about the differences with the clusters that were created for all the SPORES. This has given insight into the difference between the normal configurations and what passes as a robust configuration.

## 3.8. Robust and efficient configurations

Ultimately, decision-makers are aided by not only identifying robust energy systems but also high-performing configurations based on a set of performance indicators. For this research, the energy-efficiency of the system is used as an indicator to identify high-performing robust configurations and what addition to the common SPORE-core is needed to accomplish these configurations, step 9, 10 and 11 of the method development.

### 3.8.1. Pareto analysis

The robust clusters have told something about the most robust configuration but did not say anything about the efficiency of the energy system. To be able to answer the main research question and sub-question 3, efficiency has been taken into account. To establish what the most efficient robust configurations are, a Pareto analysis has been conducted. Pareto analysis was used to explicate dominant configurations (SPORES) on a set of specified indicators, as done in the studies by Quitoras et al. (2021) and Nehrir et al. (2011). With the two indicators, as described in section 3.2, a Pareto frontier that resembles system efficiency has been identified. Any indicator can be chosen to resemble wished-for performance, in this case, yield and curtailment were chosen to resemble efficiency. The Pareto algorithm searches for configurations which have the best trade-off, i.e. configurations that have the highest sum of yield and curtailment. The SPORES that followed from this analysis 'dominate' the other SPORES given the performance and were deemed most efficient. Similar to the research of Quitoras et al. (2021), more high-performing solutions often lay close to the Pareto frontier. To get a more complete set of high-performing configurations, a second, near-optimal Pareto frontier has been identified by disregarding the initial Pareto frontier. More or less Pareto frontiers can be calculated this way, based on what the researcher deems useful. Therefore, an overview of the performance space (i.e. visualization of indicators for all configurations) was made from which the researcher has identified if there are more configurations close to the initial Pareto frontier. Both Pareto frontiers then made up the list of high-performing configurations.

### 3.8.2. Robust and efficient core

Lastly, to be able to give insight into what additional capacity is needed on top of the common SPORE-core for robustness, the core of the robust and high-performing configurations has been determined. The common SPORE-core already has been identified and remains the same across all clusters. Additionally, per robust cluster, the minimum and maximum capacity values of each technology have been determined. The cluster core is then the collection of minimum capacity values per technology contained by that cluster. It has also been identified which robust clusters contain high-performing configurations. This resulted in robust clusters solely containing high-performing configurations. For these clusters, the minimum and maximum capacity value of each technology has been calculated. Next, a comparison has been created that shows the cluster core and maximum capacity addition on top of the SPORE-core of the robust clusters and the high-performing robust clusters. Ultimately, this comparison gives insight into what minimum capacities are a prerequisite for robustness and for robustness and efficiency.

# 4

# Results

In this chapter the results that have been generated using the method developed in chapter 3 will be explained. First, the weather year classification is explicated. After, the decision space has been visualized. Next, from the decision spaces the SPORE-core and common SPORE-core are identified, whereafter the robust configurations are identified. Together with the clusters and efficiency analysis at the end of the chapter, conclusions are drawn about the results.

## 4.1. Weather year classification

The nine historical weather years in North Sea Calliope have been classified based on the total system costs. Figure 4.1 shows the results of the overall system costs.

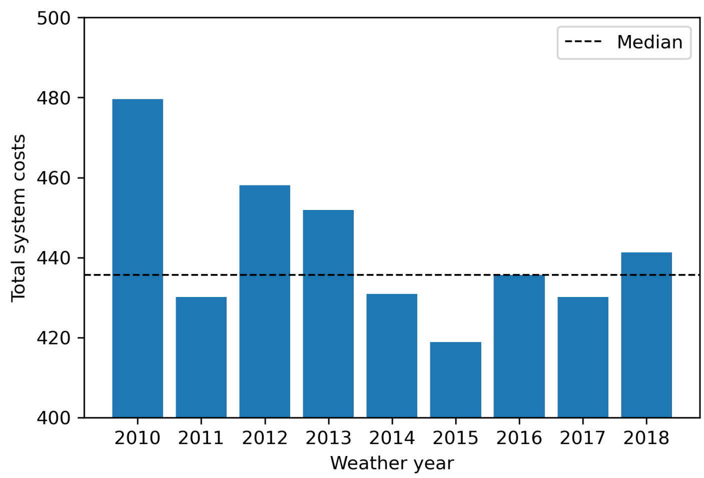


Figure 4.1: Weather year classification bar chart. The total system costs for each historic weather year of Nort Sea Calliope are shown.

From the figure, it becomes clear that 2010 is the 'worst' weather year, it has the highest overall system costs. 2016 is the median (typical) weather year, and 2015 is the weather year with the lowest overall system costs and shall be classified as the best weather year. This classification does however not yet show the make-up of the weather years. To make clear what the exact configuration of the selected weather years is, the figure below has been made.

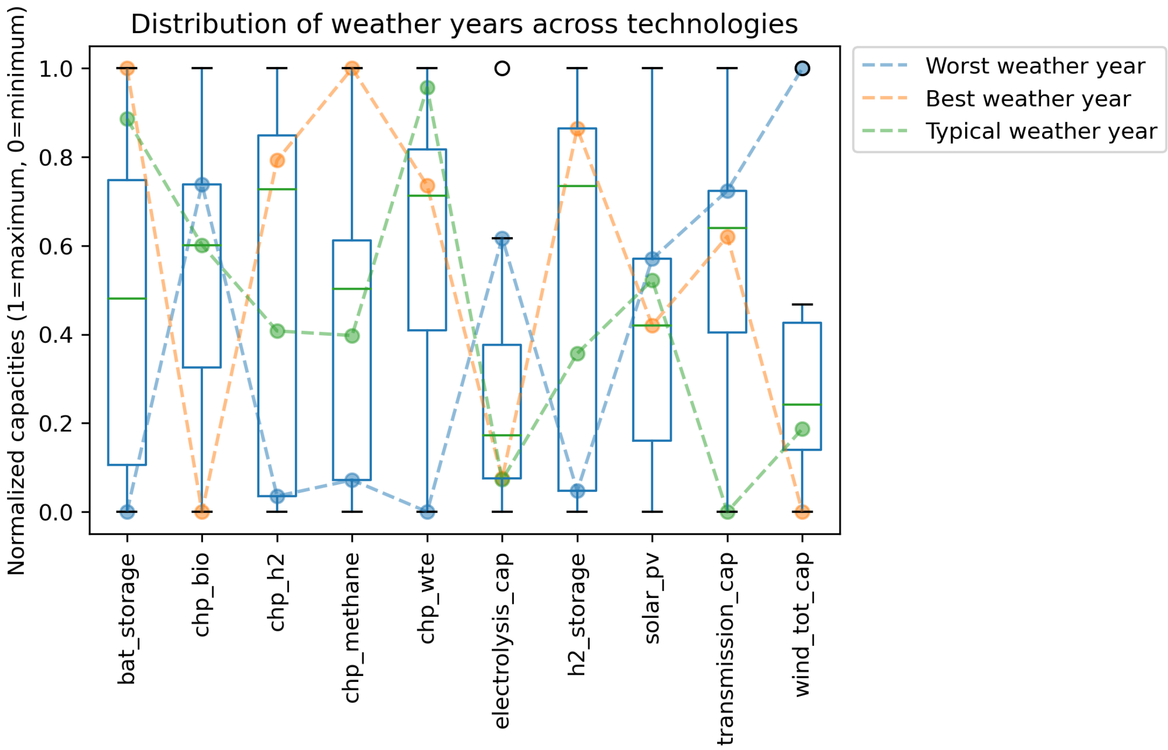


Figure 4.2: Distribution of selected weather years across all historic weather years in Nort Sea Calliope for each technology.

Figure 4.2 shows where the selected three weather years place compared to all historical weather years that are in North Sea Calliope across all technologies. The technologies have been normalized (with the minimum being 0 and the maximum being 1) to be able to compare the data. The worst weather year, 2010, has a low amount of battery and hydrogen storage capacity installed, whilst the installed capacity of electrolysis to make hydrogen is very high. When looking at the CHP capacities, in the worst weather scenario biofuel CHP has a high installed capacity while hydrogen, methane and WTE CHP capacities are very low. Additionally, renewable generation and transmission capacity are high in the worst weather scenario. Especially total installed wind power capacity is the highest of all weather years in the North Sea Calliope model.

The weather year 2015 is the best weather year cost-wise. Looking at figure 4.2, it shows that the best weather scenario has high amounts of installed storage capacity for hydrogen and battery. Electrolysis capacity, however, is on the lower side of the data. In contrast with the worst, the best scenario has low installed capacity for biofuel CHP and high installed capacities for CHP from hydrogen, methane and WTE. Moreover, solar PV, wind power and transmission capacity are on the lower side compared to the worst scenario. However, for solar PV and transmission, the best scenario is close to the median. For wind power, the best scenario has the lowest installed capacity of all North Sea Calliope weather years.

Lastly, 2016 is classified as the typical weather year. Looking at storage, the typical scenario lies between the worst and best scenario. For battery storage, the typical scenario has a relatively high installed battery capacity; for hydrogen, the capacity is on the lower side. Installed electrolysis capacity is low and at a similar level as the best scenario. Installed CHP capacities are also relatively in between the worst and the best scenario with only CHP WTE having high installed capacity. For renewable generation and transmission capacity, the figure shows that the typical scenario is in between the worst and best scenario for solar PV capacity, has the lowest installed transmission capacity and is almost at a median level for installed wind capacity.

Summarising, the worst weather year is recognized by highly implemented variable renewable capacity and low storage means. In contrast, the best weather year has relatively low variable renewable energy capacity installed but does use higher storage capacities. For the typical weather year, no extremes are shown from the data, only a relatively low installed transmission capacity.

## 4.2. Decision space

After the SPORES algorithm has been run, the decision spaces for each weather scenario and scenarios combined are divided into three sections as discussed in chapter 3.4. The first decision space plot gives insight into the main renewable generation and transmission technologies which have been shown to be of large interest to decision-makers, see section 3.2. The other two plots explicating corners of the decision space and the descriptive statistics can be found in appendix C. These tables will also be used in section 4.3 for further analysis.

Figure 4.3 shows the decision spaces for the main renewable generation capacities, solar PV and wind power, and the installed transmission capacity. The decision spaces are similar in shape. However, the best weather scenario (2015) has a lower solar PV upper bound as well as a lower total wind capacity upper bound. Additionally, the transmission capacity upper bound for the best weather year is higher and for the typical weather year is the lowest. Furthermore, when solar PV and wind both increase, more configurations with a high transmission capacity can be seen across all the weather years. The bulk of the configurations are located at a lower solar PV capacity and medium to low wind power capacity.

The decision spaces in appendix C show there exist few configurations that utilise storage. It also shows that a configuration either uses battery storage or hydrogen storage, no configurations have high capacities of both. For the CHP technologies, CHP from biofuels has a wide spread in capacity deployment and the worst weather scenario has configurations with slightly higher overall capacities of this technology. Furthermore, if CHP capacity from biofuels and methane is high in a configurations it also has a relatively high CHP from waste capacity.

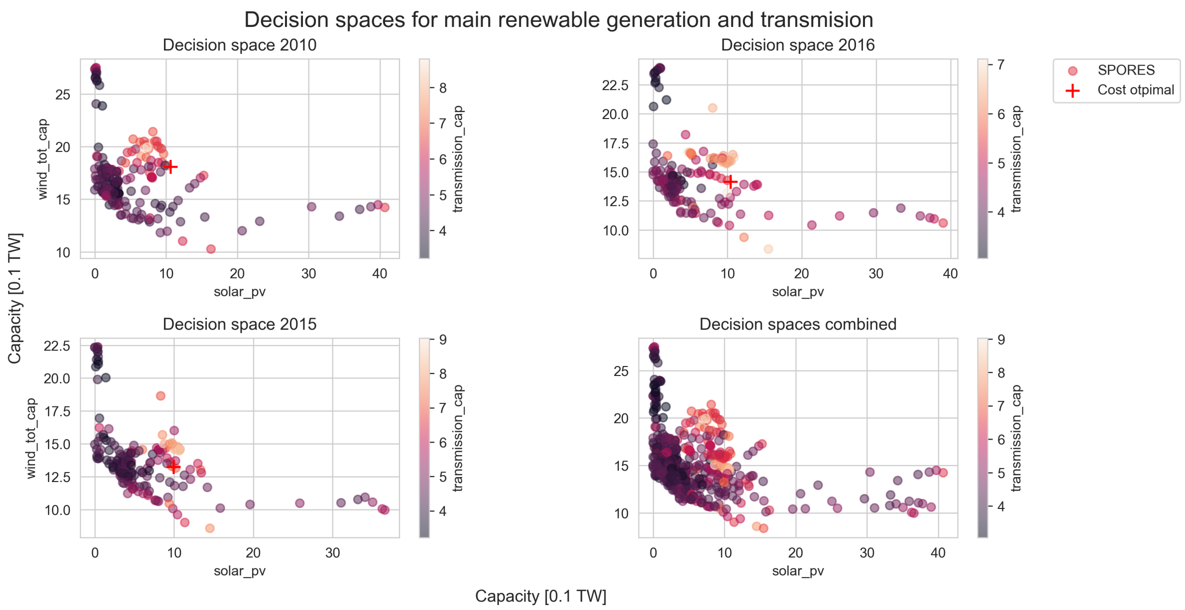


Figure 4.3: Decision spaces per weather year and for all weather years combined for the main renewable generation and transmission capacities.

Results show that transmission is generally higher when both solar PV and wind power capacity are high. Additionally, very few configurations exist with high storage capacities. For decision-making, it is evident that transmission does rise with high solar PV and wind power capacities and that only little storage is present to encounter for the renewable generation sources. Decision-makers should also take note that no configurations exist where both solar PV and wind power capacity have low capacities, meaning that both technologies have capacities in the possible decision options. Another finding about the possible decision options is that CHP from biofuels have a large decision option space, where some capacity is present for nearly all configurations.

## 4.3. The SPORE-core and common SPORE-core

As discussed in section 3.5 the SPORE-core contains all minimum capacity values of each technology per weather scenario. Table 4.1 shows the SPORE-core for each weather year. Zero values indicate that configurations exist that have zero installed capacity of said technology. If a capacity value is zero, we say that the core is empty. Non-zero values indicate that for every configuration in the decision space of the respective scenario, a minimum installed capacity exists, i.e. not a single configuration has a capacity lower than this value.

| | bat_storage | chp_bio | chp_h2 | chp_methane | chp_wte | electrolysis_cap | h2_storage | solar_pv | transmission_cap | wind_tot_cap |
|---|---|---|---|---|---|---|---|---|---|---|
| **core worst scenario** | 0.000 | 0.024 | 0.000 | 0.000 | 0.037 | 2.083 | 0.000 | 0.002 | 3.228 | 10.272 |
| **core best scenario** | 0.000 | 0.030 | 0.000 | 0.000 | 0.044 | 2.095 | 0.000 | 0.001 | 3.230 | 8.571 |
| **core typical scenario** | 0.000 | 0.000 | 0.000 | 0.000 | 0.046 | 1.953 | 0.000 | 0.001 | 3.060 | 8.362 |

Table 4.1: Minimum system capacities per technology (SPORE-core) for each weather scenario. All capacities are in in 100,000 MW (0.1 TW).

Figure 4.4 shows the minimum values of each technology in green, i.e. the core, and the maximum value for each technology in blue. It can be noted that the core values do not differ greatly between the weather scenarios. For wind power capacity it is clear that the worst weather scenario has a higher core and maximum value than the typical and best scenario. Across all configurations, wind power thus has the highest capacities when weather is not favourable. Furthermore, for both solar PV and battery storage the core values are empty or close to zero. However, the maximum capacity values for these technologies are very high, indicating that these two technologies can differ greatly when looking at possible energy system configurations. Again, the worst weather year has the highest maximum for both solar PV and battery storage.

The common SPORE-core contains the minimum capacity values of each technology over all weather scenarios, the core of the SPORE-core so to say. In table 4.2, the values for each technology can be seen that make up the common SPORE-core. The table shows that the values from battery storage capacity, CHP from biofuels capacity, CHP from hydrogen capacity, CHP from methane capacity and hydrogen storage capacity are all 0. For decision-makers, the common SPORE-core represents the so-called no-regret decisions. Meaning that no matter which weather scenario is regarded, the common SPORE-core is a minimum capacity that is always present across the configurations. For the technologies with an empty core, there are configurations of the energy system possible without that technology. However, it has been identified that there is no configuration that exists at the core of every technology. Meaning that only adapting common core capacity values will not suffice demand in an energy system and will not facilitate robustness. Therefore, in further sections, it will become clear what additional capacity decisions are needed to create robustness.

| | common SPORE-core [0.1 TW] |
|---|---|
| **bat_storage** | 0.000 |
| **chp_bio** | 0.000 |
| **chp_h2** | 0.000 |
| **chp_methane** | 0.000 |
| **chp_wte** | 0.037 |
| **electrolysis_cap** | 1.953 |
| **h2_storage** | 0.000 |
| **solar_pv** | 0.001 |
| **transmission_cap** | 3.060 |
| **wind_tot_cap** | 8.362 |

Table 4.2: The common SPORE-core. Each value represents the minimum capacity for a technology for all configurations in this research

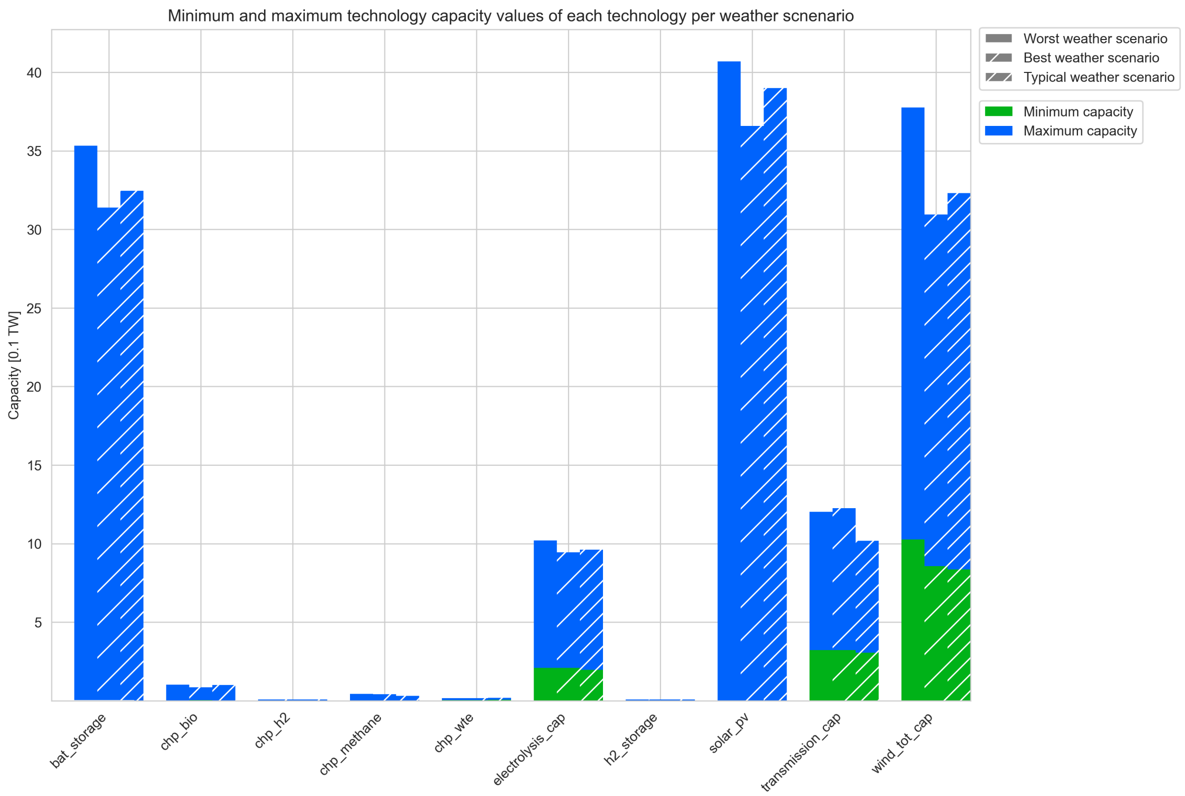


Figure 4.4: Bar chart showing the cores per weather scenario. Each bar represents the minimum capacity value of a technology for the configurations of the respective weather scneario

## 4.4. Clustering the configurations

All configurations have been clustered based on the capacity values of the technologies, as described in 3.7. This resulted in the dendrogram that can be found in appendix C. A cut-off point is chosen so that a relatively large distance between clusters remains as indicated by the black dashed line in the dendrogram. Following this cut-off point, 4 clusters remain for all SPORES. The table underneath shows the cluster names and the number of configurations that are in each cluster.

| **Cluster** | **#Configurations** |
|---|---|
| **Solar PV dominated cluster** | 18 |
| **Battery storage dominated cluster** | 21 |
| **Wind power dominated cluster** | 505 |
| **Balanced cluster** | 56 |

Table 4.3: Number of configurations per cluster for all configurations.

Figure 4.5 shows the composition of technology capacities of the 4 clusters. As can be seen, each cluster has a very distinct composition. These distinct compositions, explicated below, make for four types of energy systems that are contained in the decision option space.

1. Cluster 1: Solar PV capacity dominated the generation mix.
2. Cluster 2: Battery storage capacity is prevalent in the generation mix.
3. Cluster 3: Wind power capacity dominated the generation mix with a relatively large amount of transmission.

4. Cluster 4: A balanced generation mix with mainly solar PV and wind power as generation sources and a relatively large share of transmission.

The precise division of technologies within a cluster can be found in appendix C.4 and C.6. These boxplots show all configurations contained in a cluster, to explicate the range of technology values the configurations have within a cluster. Looking at the precise division, the solar PV-dominated cluster contains only configurations with relatively high solar PV capacity. Moreover, the solar PV-dominated cluster contains the highest shares of CHP from biofuels capacity. Regarding the battery storage-dominated cluster, the boxplots indeed show that this is the only cluster with high battery storage capacity configurations. Additionally, this cluster contains, like the solar PV-dominated cluster, relatively high capacity configurations of CHP from biofuels. The wind power-dominated cluster has the highest wind power capacity. However, the lower bound for the wind power in this cluster is fairly similar to the battery-dominated cluster. Furthermore, the wind power-dominated cluster has a lot of outliers across all technologies. Since the majority of configurations are contained in this cluster, such outliers are expected. Lastly, the balanced cluster is truly balanced when regarding the capacity values of the technologies. Compared to the other clusters, the capacities of the configurations are in between the capacities of the other clusters. Wind power does however have the lowest lower bound in this cluster and a relatively low upper bound. Almost all clusters have a very low hydrogen storage deployment, only the wind power dominated cluster has outliers with high hydrogen storage. The same goes for the CHP from hydrogen and methane. Overall, from the ten main technologies considered in this research, solar PV, wind power, battery storage and transmission largely dictate the division in energy system compositions.

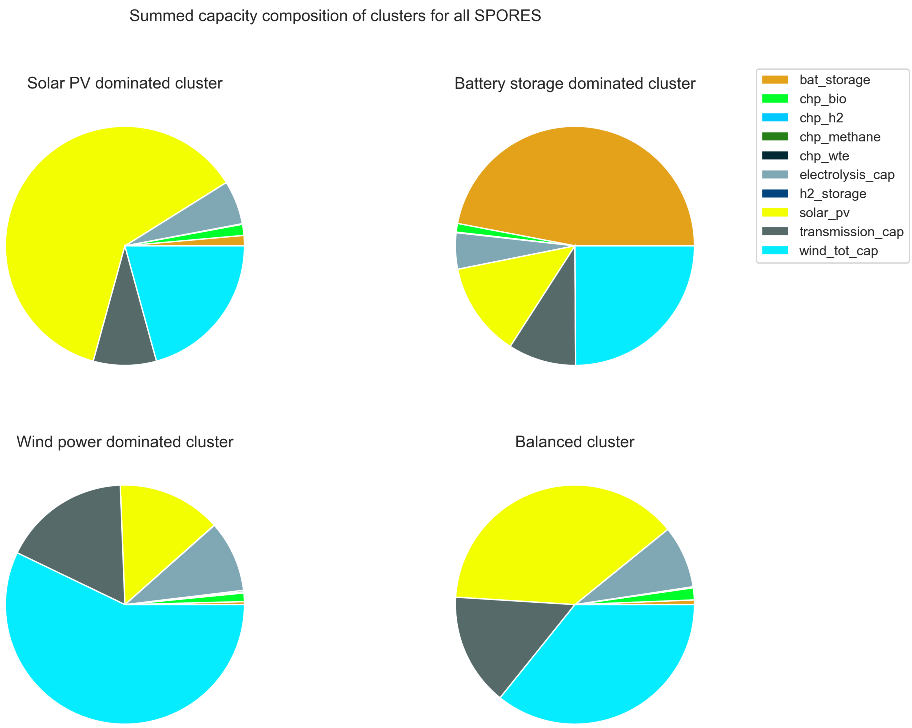


Figure 4.5: Composition of clusters for all configurations. Capacity values are summed over all configurations within a cluster per technology. A larger area in the chart indicates a higher summed capacity for the respective technology.

## 4.5. Robust configurations and clusters

All configurations have been checked for robustness with the algorithm described in chapter 3.6. After the algorithm has been run, 330 configurations remain as robust out of the original 600. To see how the composition of these configurations has changed, the clustering algorithm is run for these 330 configurations. Again a dendrogram was created with a cut-off point, see appendix C.5. Choosing relatively large distances between clusters, again 4 clusters remained. The resulting clusters and a number of SPORES that are in the clusters are described in the table below.

| Cluster | #Configurations |
|---|---|
| **Solar PV dominated cluster** | 4 |
| **Battery storage dominated cluster** | 3 |
| **Wind power dominated cluster** | 196 |
| **Balanced cluster** | 127 |

Table 4.4: Number of configurations per cluster for robust configurations.

The composition of the cluster can be seen in figure 4.6, the precise technology value range of the configurations within a cluster can be found in appendix C.6. From the pie charts, it is clear that the four identified cluster types all also exist for robust configurations. Decision-makers, therefore, are presented with four types of energy system composition when designing a robust energy system. Next, looking at the boxplots to find the range of the capacities contained in each cluster, it can be seen that the ranges of the robust clusters are smaller. The capacities in the robust cluster are generally lower by a small margin than the non-robust cluster. The battery power-dominated cluster remains similar in capacities. For the solar PV-dominated cluster, the solar PV capacity is slightly lower and wind power is slightly higher than in the regular cluster. The largest difference can be found between the wind power-dominated clusters and the balanced clusters. Where for all configurations the wind power-dominated cluster was the cluster with many outliers, for the robust clusters the balanced cluster is the cluster with a lot of outliers. Especially for the CHP from hydrogen and methane and hydrogen storage. It can also be noted that the robust balanced cluster has higher wind power and transmission capacities than the regular balanced cluster. Moreover, the wind power-dominated cluster has, for the robust cluster, slightly larger capacities of transmission and wind power and slightly less solar PV capacity than its regular counterpart. There are very few configurations that contain hydrogen storage or CHP from hydrogen. Configurations contained by the battery storage-dominated cluster are also few in number. This indicates that storage is not favourable for robust configurations, especially hydrogen storage. Rather, transmission capacities increase.

In general, the most robust configurations are contained within the wind power-dominated cluster and balanced cluster (see table 4.4). It stands out that the robust balanced cluster has more than double the number of configurations than the regular balanced cluster. Explaining the variations between the two balanced clusters. The wind power-dominated cluster loses a high number of configurations when becoming robust. This coincides with the outliers disappearing from this cluster compared to the wind-dominated cluster for all configurations. The battery storage-dominated and solar PV-dominated clusters contain 4 and 3 configurations respectively and thus provide very limited options for decision-makers.

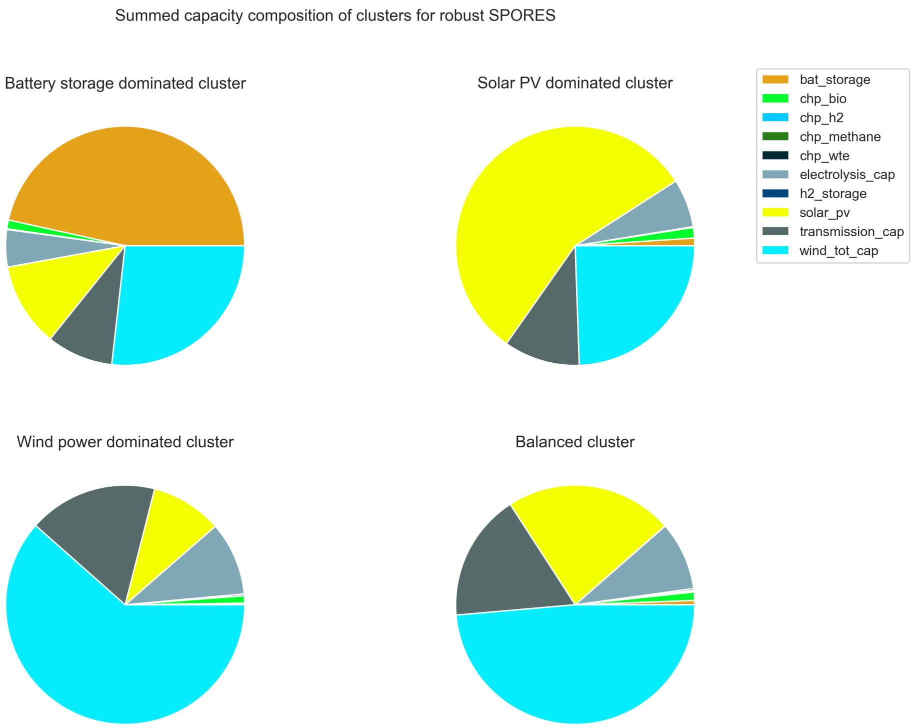


Figure 4.6: Composition of clusters for robust configurations. Capacity values are summed over all configurations within a cluster per technology. A larger area in the chart indicates a higher summed capacity for the respective technology.

## 4.6. High-performing efficient and robust configurations

To give insight into efficient and robust energy system composition all configurations have been tested for their performance on energy-efficiency. A performance space has been created by plotting the total system curtailment score (1/curtailment) against the total system yield. From this indicator space, the first set of Pareto efficient configurations has been calculated. The first set represents the overall Pareto efficient set, which contains the highest-performing energy system configurations out of all robust configurations. Figure 4.7 shows the Pareto frontiers. Since it can be noted that there are more high-performing configurations close to the initial Pareto frontier, a second Pareto frontier has been identified. This has been done by removing the first frontier and re-calculating the Pareto efficient configurations. As the results show, there is a substantial number of system configurations that are close to 0 on the curtailment score, meaning a relatively high amount of curtailment for said configurations. The Pareto frontiers all contain a relatively high system yield when compared with all the configurations. Few configurations perform both high on the curtailment score and yield and can be seen in the upper right quadrant of the graph.

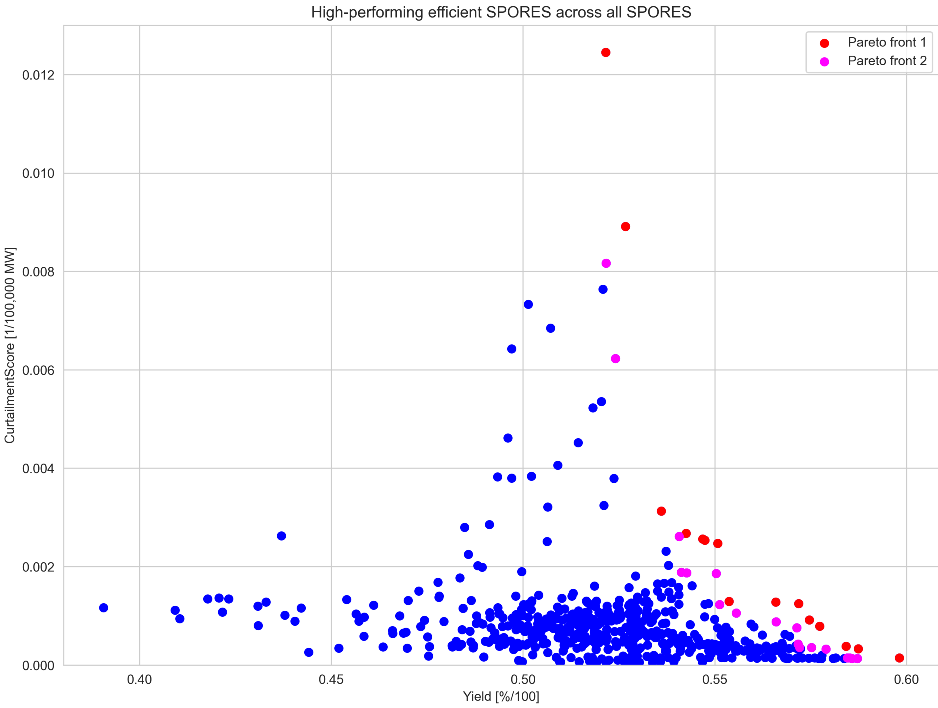


Figure 4.7: Performance graph containing all configurations with the selection of high-performing configurations represented by two Pareto frontiers.

After the Pareto frontiers have been determined for all configurations, robust high-performing configurations have been identified. To see which high-performing configurations are robust, an overview has been made explicating in which robust cluster the high-performing configurations are, if these configurations are at all robust. Some high-performing configurations were not robust and are not considered for further interpretation. Table 4.5 shows that most high-performing robust configurations are contained within the robust balanced cluster and four configurations are contained in the wind power-dominated robust cluster. These results show that 18 out of 22 high-performing configurations are in the robust balanced cluster, indicating that this system configuration is to be considered for decision-making. When designing a robust and efficient energy system it should be noted that relatively many configurations score low on the curtailment score. This means that system yield is high, thus the installed capacity is generating energy efficiently, but a share of this energy will not be delivered to the grid but thrown away.

| **Robust cluster** | **# robust high-performing SPORES** |
|---|---|
| **Wind power dominated cluster** | 4 |
| **Balanced cluster** | 18 |

Table 4.5: Number of high performing configurations in the robust clusters

Next, the precise composition of the high-performing robust configurations is explicated. The figures in appendix C.7 show the visualized composition of these clusters. The configurations contained by the first Pareto frontier have similar compositions. Each configuration contains wind power as the main installed renewable capacity. Additionally, solar PV is also installed in all configurations but can vary between medium and low installed capacity. Each configuration contains a similar share in electrolysis capacity and a similar share of CHP from biofuels. Taking the second Pareto frontier into account, similar configurations can be found. For a number of the second Pareto frontier robust configurations, the results show small amounts of installed battery storage capacity. Energy systems that perform well given the robustness thus always include solar PV and wind power as the largest renewable generation capacities, but this does not yet state what minimum investment in these capacities in needed for robustness. The following section will explicate what is minimally needed to facilitate robustness and efficiency.

## 4.7. Robust and efficient cores

The common SPORE-core represents the no-regret decisions for capacity investments. However, this does not constitute robustness and efficiency. Here, insight is given into what additional capacity contribution is needed to provide robustness. Additionally, insight is given into what additional capacity contribution on top of the common core is needed for robustness and efficiency. For this, the core of the wind power-dominated and balanced robust clusters have been determined since these are the only two robust clusters that contain high-performing configurations. This has been done by taking the minimum capacity value for each technology per robust cluster. The maximum contribution has also been determined by taking the maximum value of each technology per robust cluster. This has also been done for the high-performing configuration per respective cluster. Figure 4.8 shows the contributions on top of the common SPORE-core for the wind power-dominated robust cluster and the contribution of the high-performing configurations in this cluster, in appendix C.8 the two graphs can be found with a logarithmic y-axis to better show the small capacity cores. When looking at the technologies for which the common core was empty, it stands out that CHP from biofuels has a minimum addition on top of the core. Meaning for robustness, CHP from biofuels needs to be present. When looking at the high-performing configurations, even a higher minimum contribution is needed for CHP from biofuels. Solar PV had a very small common core value and for robustness the minimum required capacity remains very low. However, for the high-performing robust configurations, a substantially large minimum capacity for solar PV is needed. Therefore, results show that a robust and efficient energy system needs a large additional capacity of solar PV. Results also show that wind power needs additional capacity on top of the common core. The robust and efficient configurations need slightly more minimum capacity than solely the robust configurations. What stands out is that the maximum contribution of wind power for the efficient and robust configurations is very close to the minimum required addition.

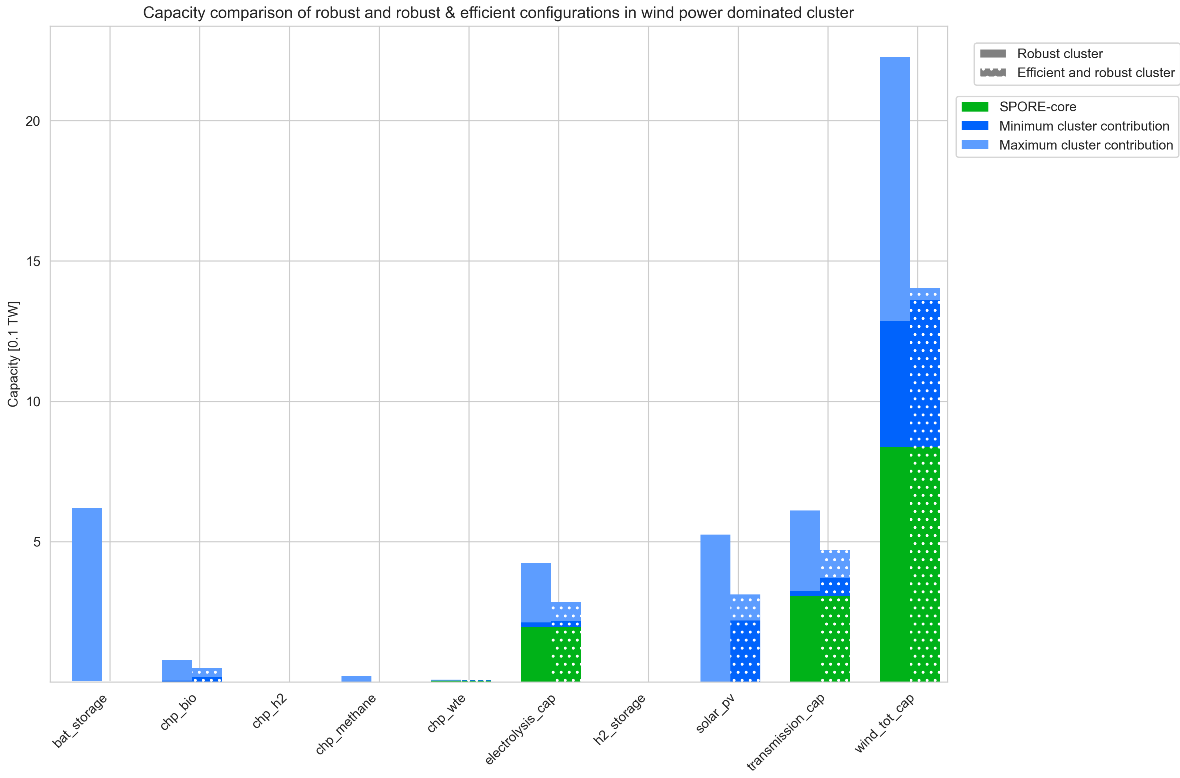


Figure 4.8: Bar chart showing the common SPORE-core per technology with the minimum and maximum capacity of the robust wind power dominated cluster. The left bars show the minimum and maximum values of the robust cluster per technology. The right bars show the minimum and maximum values of the high-performing configurations in the robust wind power dominated cluster per technology. A dark blue bar means there is additional capacity needed on top of the common SPORE-core.

Figure 4.9 shows the capacity contributions on top of the common SPORE-core for the balanced robust cluster and the high-performing efficient configurations in this cluster. For technologies with an empty common core, the finding is the same as for the wind power-dominated cluster. Looking at solar PV for the robust and efficient and robust configurations in this cluster a substantially larger minimum capacity is needed when compared to the common core. The balanced cluster, therefore, also shows that in order to become efficient and robust, a minimum solar capacity is needed in this case just above 0.25 TW. For the balanced robust cluster additional wind capacity is present on top of the common core, be it less than in the wind power-dominated cluster. Transmission capacity is also added to the common core, where robust and efficient configurations have a higher addition than solely robust configurations.

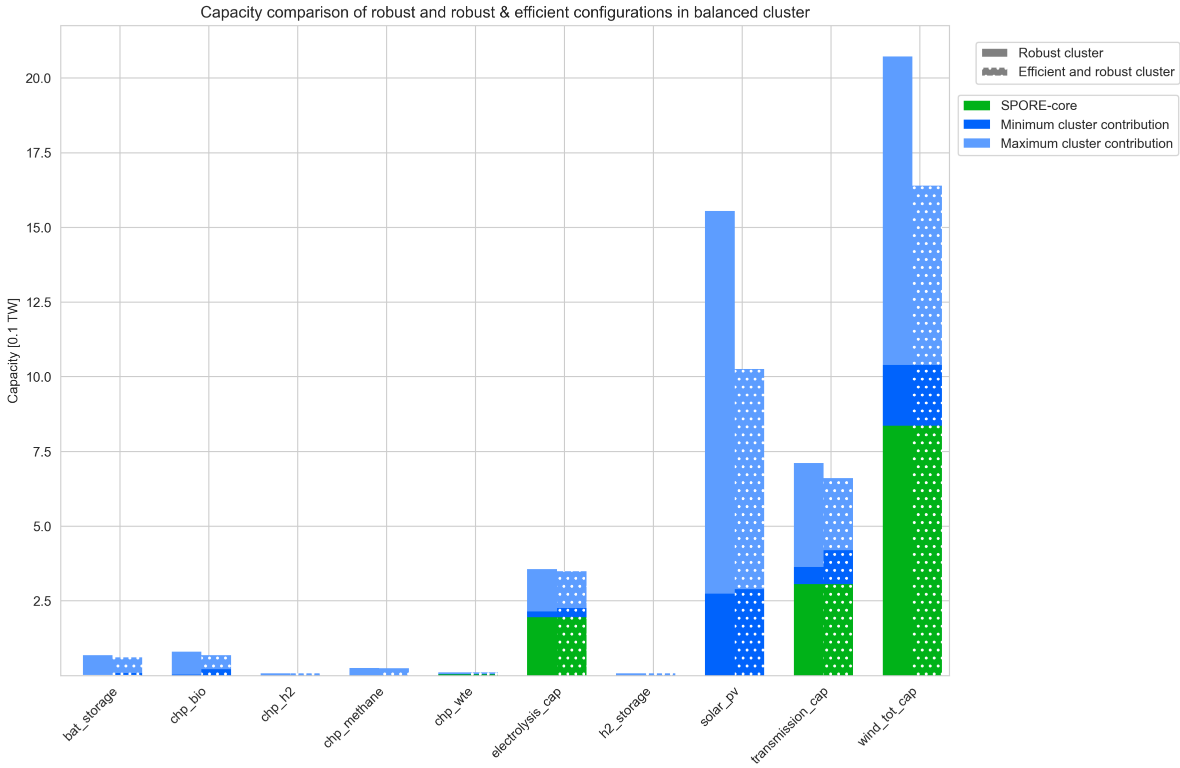


Figure 4.9: Bar chart showing the common SPORE-core per technology with the minimum and maximum capacity of the robust balanced cluster. The left bars show the minimum and maximum values of the robust cluster per technology. The right bars show the minimum and maximum values of the high-performing configurations in the robust balanced cluster per technology. A dark blue bar means there is additional capacity needed on top of the common SPORE-core.

The above figure shows that additional capacities are needed on top of the no-regret decisions to become robust and efficient in this research. Wind power and solar PV are the main renewable generation sources and a minimum capacity of these technologies needs to be present for a robust and efficient system. Moreover, transmission also shows additional needed capacity when robustness and efficiency are considered. In contrast to tranmission, the storage mediums, especially hydrogen storage, have a very low capacity in the robust and efficient energy systems. Results indicate that no-regret decisions, namely the common SPORE-core, do not constitute robustness and efficiency. When the aim is to become robust to weather fluctuations and increase system efficiency (i.e. higher yield and lower curtailment) additional investment in CHP from biofuels, electrolysis, solar PV, transmission and wind generation capacity is a prerequisite.

# 5
# Discussion

## 5.1. Introcution

The aim of this research has been to develop a method that uses the SPORES methodology to give insight to decision-makers into the composition of robust and efficient energy system configurations given weather uncertainty. Through systematically and selectively (due to computational constraints) covering the weather decision space of the North Sea Calliope model with the use of SPORES, a variety of possible energy system configurations have been created. The created method was then applied to the decision spaces to identify robust and efficient configurations. The following findings stand out.

## 5.2. Answering and reflection

### 5.2.1. Method for identifying robust energy systems

The first part of this research aimed at developing a method to give insight into robust energy system designs. For this, the SPORES methodology has been utilized to maximize the diversity of the decision options space based on the technologies chosen in this research. As Mens et al. (2011) explained, robustness means that a system keeps functioning even though the system faces disturbances. Therefore, this method has focused on identifying configurations that have a capacity value within every weather scenario for every technology. Configurations within this range were proven feasible across all tested weather scenarios in this research. Using this method, decision-makers are presented with a multitude of options that ensure feasibility under the presented weather scenarios. When robustness and efficiency were both taken into account, the results have shown that balanced system configurations are favourable. A possible explanation for this is that the developed method ignores the extreme configurations because the robustness search method ensures that configurations lay within the maximum-minimum and minimum-maximum capacity values of every technology across the weather scenarios. Decision-makers are thus presented with configurations that exist throughout all weather scenarios, making these configurations robust decision options out of the decision space presented in this research.

### 5.2.2. Composition of robust energy system configurations

This research has further focused on identifying the composition of robust energy systems. First, no-regret decisions across the whole decision space were identified to eventually give insight into what additional capacity is needed for robust energy systems. Results have shown that technologies exist where the no-regret decision option is to not install capacity. This does however not mean that the no-regret capacities will suffice demand in the future energy system. Rather these decision options show that there is a minimum required capacity that should be installed regardless of weather fluctuations for the future energy system. From the no-regret decisions, it has become clear that the energy system of the future needs CHP from WTE, electrolysis, solar PV, transmission and wind power capacity. Wind power has proven to be controversial for multiple stakeholders in the North Sea region. It also has the highest value of all technologies for no-regret decisions, meaning decision-makers need to face a future energy system design where wind power is an absolute prerequisite. Since the no-regret decisions represent the minimum required capacity investments, these decisions are dictated by the scenarios where the weather circumstances were the most advantageous for the technologies. The worst weather scenario is the most costly scenario and does not dictate the no-regret decisions. Decision-makers should therefore take note of the fact that no-regret options do not facilitate weather robustness.

Robustness means that additional capacity investment decisions have to be taken by decision-makers on top of the no-regret decisions. Especially solar PV needs large additional capacity investments in order for energy systems to become robust to weather fluctuations. Wind power needs additional capacity to be present for a robust energy system. The largest generation technologies of a robust and efficient North Sea energy system are, therefore, solar PV and wind power. Transmission capacity requires additional capacity investments if the aim is to become more robust. The latter can be explained by the large wind power and solar capacity. High penetration of wind power and solar PV in future energy systems means that grid capacity has to be increased to account for the fluctuations these sources bring (Bird et al., 2016). What stands out is that the storage technologies have very low capacity values, especially hydrogen storage. This research shows that the favourable decision for robustness is to implement more transmission and not rely on storage technologies to mitigate weather fluctuations. A possible explanation is that storage technologies are relatively expensive. Battery storage is projected to have higher costs than hydrogen storage (Kharel & Shabani, 2018) and hydrogen storage itself is also a relatively expensive technology in the current market (Loisel et al., 2015). Additionally, electrolysis capacity is present in the no-regret decisions and needs a small capacity increase for robust energy systems. Hydrogen, therefore, is present but not for storage means, meaning hydrogen is used in other sectors as an energy carrier.

That robustness implies that additional capacities are needed is in line with the literature. Gabrielli et al. (2019) showed that with increasing robustness, whilst lowering $CO_2$-emissions, system costs increased. Additionally, results showed that CHP from biofuels is present in robust energy system configurations, in contrast to the no-regret decisions. Palzer and Henning (2014) also showed that a 100% renewable energy system with large capacities of wind power and solar PV has to be accompanied by CHP technologies. Moreover, Palzer and Henning (2014) show that CHP technologies should be added to meet demand when grid capacity is restricted. The presence of CHP in robust energy system configurations can be explained by the need for predictable power generation when the grid is congested or renewable production is low. Concluding, when designing a robust future energy system, this study shows that a balanced energy system is to be considered by decision-makers.

### 5.2.3. Robust and efficient energy system configurations

Not only the robustness of a future energy system but efficiency was also considered a key factor for decision-makers. Results showed that, when efficiency is taken into account, solar PV, wind power and transmission need a slightly higher capacity investment than solely robust energy systems. Moreover, efficient and robust configurations were only made up of balanced configurations. This shows that decision-makers only have to regard balanced energy system designs when wanting both a robust and efficient energy system. Similar to the robust configurations, more capacity investment is needed when weather uncertainty is accounted for. The study of Quitoras et al. (2021) showed that increasing robustness, whilst regarding high-performing configurations with Pareto frontiers, caused the objective function of the multi-objective optimization to shift to a higher cost optimal outcome. It should be noted that robust and energy-efficient energy system designs require more investments by decision-makers than designs where various weather scenarios are not regarded.

An additional finding is that the majority of robust and efficient configurations contained large capacity shares of offshore wind power, compared to onshore wind power. Offshore wind energy production, in comparison to onshore wind, has an environment of more stable and high wind speeds which means a more stable high power output (Li et al., 2020) and the water surface provides less friction thus offshore wind has a higher wind energy potential (Kucuksari et al., 2019). A more stable and high power output also means the yield of a wind farm is higher since less redundant capacity needs to be installed. Moreover, the capacity factor of offshore wind power is also generally higher than the capacity factor of onshore wind power (International Energy Agency, 2019d). This explains why offshore wind power is more prevalent in efficient and robust configurations. It should be noted that all high-performing robust configurations stemmed from the typical weather scenario, which was generally a good weather scenario for wind power. Results showed that the typical weather scenario was an almost median wind power capacity year. However, following the literature, offshore wind can still be deemed more promising for high efficiency in future energy system designs than onshore wind power.

### 5.2.4. Robust and efficient energy systems given weather uncertainty

Decision-makers can use the methods presented in this research to identify robust and efficient future energy system compositions. Where Energy System Modelling mostly uses a single weather year, this research has provided a method with which a multitude of weather scenarios can be taken into account. Applied to the case of the North Sea region results showed that solar PV, offshore wind power, transmission, electrolysis and CHP from biofuels capacity are key to a robust and efficient energy system. For solar PV, the results showed that configurations exists where the installed capacity is near zero. However, to become robust and efficient, a large increase in the installed capacity of solar PV is needed. In the context of the North Sea energy system, decision-makers are presented with minimum capacity requirements for robustness and efficiency. Especially wind power causes controversy, but this research has shown that a large share of wind power capacity, especially offshore, can not be ignored when trying to account for the impact of weather uncertainty. Current developments show that decision-makers do not shy away from large offshore wind capacities in the North Sea (Gusatu et al., 2020), which is in line with this research.

## 5.3. Limitations and future research

The conducted research has its limitations. Firstly, the North Sea Calliope represents the North Sea region (NSR) countries largely aggregated with a single node per country. Weather is not measured nationally, but can vary locally as well. This means that weather fluctuations have been captured with a high level of aggregation in this study and results can differ when enlarging the spatial resolution. The method created in this research can, however, be used to process more detailed data and can also easily be adapted to contain larger spatial and temporal details.

Secondly, a further level of aggregation is applied in the data analysis phase of this study. All values of the generation technologies have been aggregated over the available countries in the model, meaning the technologies are represented with one value for the whole North Sea energy system. Here, another layer of precision on weather data is lost. Weather can fluctuate heavily between countries. The resulting configurations presented in the study do not imply a spatial distribution of capacities. When decision-makers want to use this study to design location-specific generation capacities, the data need to be deconstructed to a national scale. This study does however provide a first recommendation of the type of configurations that constitute a robust energy system.

Thirdly, with current climate change trends, the weather could become more extreme in the coming years. This study had access to nine historical weather years on which the worst, typical and best weather years are based. A larger set of historical weather years would add to the precision of the robust configuration identification. Since weather years are fairly limited, insights for decision-makers are limited as well.

Even though the case discussed in this paper does not yield precise conclusions about the makeup of a robust and efficient future energy system, it does propose a thorough method for identifying promising configurations to be used in further analyses. This study gives a direction for robust and efficient energy system configurations. On this first iteration, future research can elaborate.

First, future research can focus on expanding on the method used in this research. This method can serve as a pre-selector for identifying the most-promising robust energy system configurations for any set of chosen performance indicators. Future research can thus use the identified robust and efficient configurations for further weather year testing by simulating the single configuration over a multitude of weather years. By doing so, future research can explicate if the identified configurations remain high-performing and robust across a larger scale of weather scenarios. This will strengthen the insights for decision-makers. An attempt was made during this research to test single configurations for a multitude of weather years, however, since the complexity of the Calliope model and user constraints of the used computing cluster, the solutions did not converge. Further research should take this into account when testing a single configuration, possibly alternative solver algorithms need to be used.

Furthermore, future research can focus on diversifying the region this method is applied to. This study has used the North Sea region as an example. The question remains what a robust and efficient energy system configuration constitutes in different regions. For example, the southern part of Europe is different in climate than the northern part. Future research can therefore focus on gathering the specific input data of various regions to analyse how robust and efficient energy system configurations change through various climates. All in all future research could use the created method and scale it to contain more detail and analyse various regions of the world to explicate energy system robustness.

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# A

# Appendix - Background and Stakeholders

In this appendix, the background and stakeholder and country needs are further explicated.

## A.1. Modelling to Generate Alternatives and Spatially Explicit Practically Optimal Results

Energy System Modelling through optimization is faced with major uncertainties, such as weather. Chasing a single solution with ESM can be “misleading” as J. F. DeCarolis et al. (2016) put it. The focus should therefore be on generating multiple alternative configurations to generate more valuable insight (J. F. DeCarolis et al., 2016). One method of ESM to systematically explore the decision space is Modelling to Generate Alternatives (MGA). More specifically, MGA generates very different energy system configurations so that the decision space is properly mapped (J. F. DeCarolis et al., 2016). Decision-makers particularly benefit from modelling near-optimal solutions, because decision-makers often do not choose the cost-optimal solution due to other political, social or environmental factors (Prina et al., 2023). Lombardi et al. (2020) even state that, due to the uncertainty, future energy system configurations within 10% of the economic optimum are hard to distinguish from the optimal solution for decision-makers. To give insight to decision-makers, MGA can be formulated in many forms for modelling (J. F. DeCarolis et al., 2016).

A method of implementing MGA is the Spatially Explicit Practically Optimal Results (SPORES) methodology. SPORES differ spatial deployment of technology in the energy system model. SPORES is currently being deployed in the Calliope energy system model (Lombardi et al., 2020). SPORES are, however, different from usual MGA methods. Where MGA tries to make as different as possible configurations based on assigning penalties on energy technology capacities, SPORES takes the spatial deployment of various energy technologies into account (Lombardi et al., 2022). An example from (Lombardi et al., 2022) states that MGA will penalise wind generation in general if it is highly used in the cost-optimal solution and SPORES will only penalise based on the spatial deployment of the technology, so per location, a separate penalty exists. Figure 2.1 provides an overview of the SPORES workflow.

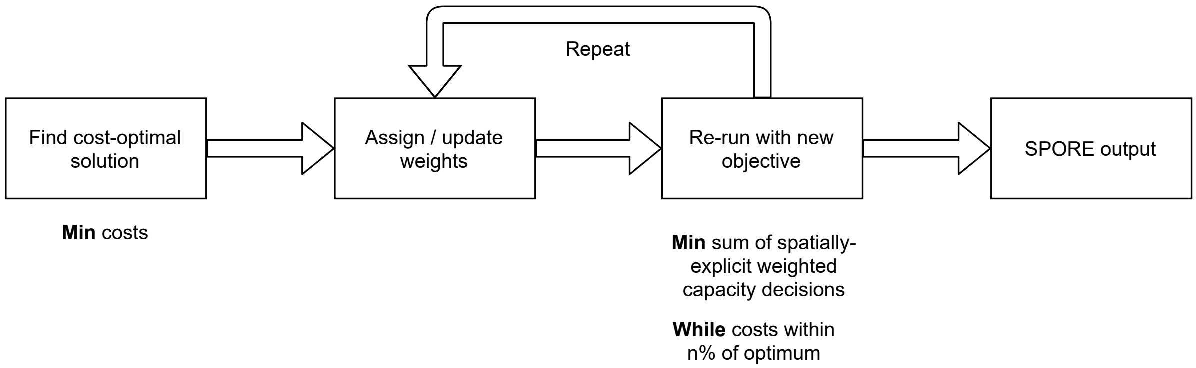


Figure A.1: SPORES workflow adapted form Lombardi et al. (2022)

The figure shows that the SPORES workflow will first determine the cost-optimal solution. After, weights are assigned to the generation capacities per location. Next, the model is optimized again, but the cost constraint is relaxed so that the total system costs are within a given percentage of the system costs of the optimal solution. This will result in a model configuration, denoted by the 'SPORE output' box. For the next run, the weights (or penalties) are updated based on the previous run and the cycle is completed once again. This cycle will be completed as many times as the modeller wishes.

To understand how the SPORES are composed in the model, the mathematical formulation needs to be understood. First, Lombardi et al. (2022) explain how the weights are assigned in the 'normal' method in equation A.1. Here a weight is assigned based on the weight of the previous model iteration for technology $i$ and location $j$ ($w_{ij}^{n-1}$). For the first SPORE the previous iteration is the cost-optimal model. To this, a division of the deployed capacity of technology $i$ at location $j$ over the maximum possible capacity of technology $i$ at location $j$ is added ($\frac{x_{ij}^{cap,n}}{x_{ij,max}^{cap}}$). So if a capacity is nearing its potential maximum, the weight (or penalty) assigned to the following iteration is large to broaden the decision space.

$$w_{ij}^{n} = w_{ij}^{n-1} + \frac{x_{ij}^{cap,n}}{x_{ij,max}^{cap}} \tag{A.1}$$

Next, to get a SPORE the whole model needs to be subject to a minimization. Lombardi et al. (2022) explain how a SPORE is created with equation A.2. For each technology $i$ at location $j$, the weight is multiplied by the capacity for that technology at that location. This is done for each location and the minimum is taken. There are constraints to take into account. The system costs cannot be larger than the given margin of the system costs ($(1+s) \cdot costs_0$).

$$min\ Y = \sum_{j}\sum_{i} w_{ij} x_{ij}^{cap} \tag{A.2}$$

$$s.t. \quad cost_n \leq (1+s) \cdot cost_0$$
$$\mathbf{Ax} \leq \mathbf{b}$$
$$\mathbf{x} \geq 0$$

The above-mentioned method does, however, struggle to explore the whole decision space (Lombardi et al., 2022). To dive deeper into the corners of the decision space, Lombardi et al. (2022) have extended the SPORES algorithm, as seen in equation A.3. They do so by adding an extra capacity decision variable. Moreover, two additional weights are added ($a$ and $b$) that can be modified as needed by the modeller. This objective function can either be minimized or maximized, depending on which corner of the decision space is to be explored.

$$min\ (or\ max)\ Y_{2,\bar{i}} = a \cdot \sum_j x_{\bar{i}j}^{cap} + b \cdot \sum_j \sum_i w_{ij} x_{ij}^{cap} \tag{A.3}$$

$$s.t. \quad cost_n \leq (1+s) \cdot cost_0$$
$$\mathbf{Ax} \leq \mathbf{b}$$
$$\mathbf{x} \geq 0$$

Lombardi et al. (2022) discuss various methods of assigning weights. The mentioned method explicated in equation A.1 is called “relative-deployment”. The other methods mentioned are the “integer” (equation A.4), “random” (equation A.5) and “evolving average” (equation A.6). Where integer is the simplest method, because either a weight of 100 is added if the capacity is above a certain threshold to avoid marginal deployment of capacity receiving a penalty. The random method assigns a random weight without an underlying rationale. Lastly, the evolving average assigns a weight based on the distance to the average capacity deployment and keeps better track of the deployment of previous iterations (Lombardi et al., 2022).

$$w_{ij}^n = w_{ij}^{n-1} + k_{ij}, \quad with\ k_{ij} = \begin{cases} 100,\ if\ x_{ij} > c \\ 0,\ if\ x_{ij} \leq c \end{cases} \tag{A.4}$$

$$w_{ij}^n = w_{ij}^{n-1} + r_{ij}, \quad with\ r_{ij} = U(0, 100) \tag{A.5}$$

$$\begin{cases} w_{ij}^n = \left| \frac{\overline{x_{ij}}^{cap,n-1} - x_{ij}^{cap,n}}{\overline{x_{ij}}^{cap,n-1}} \right| \\ \overline{x_{ij}}^{cap,n-1} = \frac{\sum_{n=1}^{n-1} x_{ij}^{cap,n}}{n-1} \end{cases} \tag{A.6}$$

## A.2. Stakeholder and country needs

The energy system of the NSR knows a variety of stakeholders. Governments and policymakers can be found at the top of the hierarchical chain. The European Union is the most profound powerful actor since the EU has the power to impose supranational legislation on member states concerned with the design of the North Sea energy system. Member states of the EU have slightly less power, due to the fact that not all member states can directly form the policy for the North Sea energy system. The interest of the member states is distributed, some member states are more heavily invested in the design of a renewable energy system than others, who are more reliant on conventional generation options.

Regarding the oil and gas (O&G) industry stakeholders, their current business is in danger when renewing the North Sea energy system. These stakeholders are dependent on fossil sources for their income, but oil and gas rigs face dismantling (Ducrotoy & Elliott, 2008) and wind power is taking over in the North Sea (Cleijne et al., 2020; Maas et al., n.d.) . Therefore, O&G stakeholders are exploring ways to lower carbon emissions (Maas et al., n.d.). Their main focus in doing this lies with carbon capture and storage (CCS) and hydrogen production. For this, the O&G companies want to use the existing infrastructure. O&G stakeholders do therefore not focus on other means of renewing, such as solarPV and wind, however, their financial means and knowledge can prove useful in the transition of energy carriers such as hydrogen.

Stakeholders with less power but relatively mediocre to high interest include the citizens, NGOs and other industries. Other industries are the industries that have some form of interest in the North Sea and its energy system. Most notable is the fishing sector of the different North Sea countries. Fishermen from the Netherlands point out that the construction of offshore wind parks takes away valuable fishing grounds (Hatenboer et al., 2023). NGOs argue that the wind parks are constructed in areas such that biodiversity is protected and that fishermen can not relocate their activities to biodiverse and protected areas (Hatenboer et al., 2023). According to the article of Hatenboer et al. (2023), citizens see the discrepancy between the fishermen and NGOs and worry about the local industry. This is a single example of the perspective of other industries in the North Sea region. One common denominator is that wind parks often play a central role in conflicts (Schillings et al., 2012).

Member states of the EU form very impactful and important stakeholders in the designing of the North Sea energy system. Underneath, per NSR country an overview of the current status and recommendations as according to the International Energy Agency (IEA) is given.

### A.2.1. Norway

Norway is a NSR country that has great natural abilities to produce renewable energy due to its landscape features. Large amounts of hydro-power cause Norway to have large amounts of renewable electricity production EU (International Energy Agency, n.d.-e). Norway, however, produces and exports large amounts of oil and gas. Therefore, the IEA recommends that Norway uses its natural capacities for renewable generation, builds additional offshore wind and transforms its income dependency to low-carbon energy carriers in order to meet a long-term vision of renewability (International Energy Agency, 2022b). Moreover, Norway is to continue increasing its electrification of high-emitting sectors, such as the transport and heating sectors. Cost-effectiveness should be evident in the policy that Norway put out. Additionally, hydrogen is a technology that bears great potential for Norway to utilise in the transition.

### A.2.2. Sweden

As for Norway, Sweden is amongst the North Sea countries that already use a lot of renewable sources for their energy supply. The Swedish energy system is reliant on hydropower and nuclear power (International Energy Agency, n.d.-f). Only a small percentage of the Swedish energy supply stems from fossil power, but Sweden targets to have 100% carbon-neutral electricity generation in 2040. The IEA recommendations for Sweden are therefore limited. The IEA echo's that Sweden should prioritise cost-effective policies across sectors. Additionally, recommendations for Sweden are to stay neutral in policy towards generation technologies and explicate the long-term vision and seek the cooperation necessary to achieve this (International Energy Agency, 2019a). Meaning that Sweden should be open to incorporate a broad scala of generation technologies that quickly could grow in innovation and market share (such as solarPV and offshore wind).

### A.2.3. Denmark

Denmark is different from the other mentioned Scandinavian countries because the energy generation mix is for the majority based on fossil fuels (International Energy Agency, n.d.-b). Denmark, therefore, has a larger task at hand. The country is however making large strides towards sustainability. Denmark is not set on a single policy or technology to achieve this. The recommendation from the IEA and an independent energy commission is to be more streamlined in policy and strategy making, meaning regional strategies are to be made and the most cost-effective alternatives should be chosen (International Energy Agency, 2017).

### A.2.4. Germany

Moving more to the western part of Europe, geographical features to produce energy are less accessible. Germany therefore still relies on large amounts of fossil fuels for its energy (International Energy Agency, n.d.-d). The electricity sector is moving towards a large share of renewables in the form of wind, solar and nuclear energy of which the latter is being phased out. Other sectors, such as the transport and heating sector, are far away from meeting sustainability goals. Germany has, therefore, been given some strong recommendations by the IEA (International Energy Agency, 2020a). First, since Germany is mainly focussing on wind (on- and offshore) and solar, which have high generation variability, large amounts are needed and thus transmission lines need a thorough capacity upgrade. Next, energy usage and demand needs to be changed. Industrial sectors need to be coupled more easily. Demand needs to be lowered by, for example, offering more diversified and progressive transport means.

### A.2.5. Great Britain

Great Britain is reviewed plus Northern Ireland, thus the United Kingdom (UK) will be analysed here. The energy sources in the UK are diverse. A major carbon reduction has been realised by replacing nearly all coal generation with natural gas generation (International Energy Agency, n.d.-h). Moreover, offshore wind is gaining traction and has a substantial market share. Additionally, the UK is dependent on mainland of Europe for energy trade. Because of Brexit, the UK should not only focus on its internal market but also on maintaining trade relationships with the continent. The IEA recommends that the UK, like Germany, focuses its attention towards the heating and transport sector since less significant decarbonisation is reached there (International Energy Agency, 2019b). Additionally, the impact of exiting trade deals of the EU should not impact the nuclear generation outlook. Overall the decarbonisation of the energy sector is developing in the right direction, but specific sectors do have to make a notable change.

### A.2.6. Ireland

Ireland is among the member states that are not on track to meet the set-out reduction goals. Although almost 25% of electricity comes from wind, other sectors are failing to mitigate emissions. Especially the transport and heating sector fail to decarbonise. When looking at the IEA recommendations, it becomes clear that Ireland is not giving certainty in decision-making which leads to unsettled policies and hesitation from investors (International Energy Agency, 2019c). Ireland, therefore, needs to develop clear roadmaps, especially on how to make the heating sector more sustainable.

### A.2.7. The Netherlands

The Netherlands are not on track to meet the emission reduction goals. This is mainly due to the high dependency on fossil fuels in the energy sector (International Energy Agency, n.d.-g). The electricity sector is slowly implementing wind and solar, but the major generation sources remain coal and gas. Not a single sector is majorly outperforming another when it comes to decarbonising. That is why the IEA recommends that the Netherlands not only speeds up its transition, but the country should also open its door to novel innovations and offer the right conditions for these innovations to enter the existing markets (International Energy Agency, 2020c). Additionally, the Netherlands is being encouraged to look at its role as the possible front-runner in hydrogen energy and hydrogen hubs.

### A.2.8. Belgium

Belgium has a lot of similarities to the Netherlands. Belgium is also greatly dependent on fossil fuels in all its sectors. The electricity sector does have renewables in the form of offshore wind and solar and a large share of nuclear power (International Energy Agency, n.d.-a). Belgium's policy is focusing on implementing more offshore wind and solar and electrifying its industry and transport sectors. The recommendations of the IEA put forward are therefore firstly aimed at cementing the emission reduction goals, set by the EU, in the national legislation (International Energy Agency, 2022a). Secondly, since Belgium seeks to add offshore wind and electrify its sectors accordingly, the transmission system ought to be upgraded to maintain a sufficient and safe electricity supply.

### A.2.9. Luxembourg

Luxembourg is the smallest country that will be discussed. Because of its size and geographical features, Luxembourg is heavily dependent on importing energy from other countries such as Germany and France (International Energy Agency, 2020b). Furthermore, Luxembourg is dependent on fossil fuels for its energy supply. Especially the transport sector is emitting a lot of carbon dioxide. The IEA has therefore put forward some key recommendations (International Energy Agency, 2020b). Luxembourg has to examine its transport sector and see where efficiency gains lay and implement those. Furthermore, the country should make a coherent framework on how to achieve the 2030 goals for all its sectors and regions.

### A.2.10. France

France has a fairly unique energy mix. On the one hand, France produces the majority of its electricity from nuclear power plants, meaning it is low in carbon (International Energy Agency, n.d.-c). On the other hand, France has a large dependency on fossil fuels for its remaining energy sectors, especially the transport sector. Since the ageing of the nuclear power plants also comes into play, France is not on track to meet the set out EU reduction targets. The IEA recommends key policy changes for France (International Energy Agency, 2021). Focus on the cost-efficiency of the transition, whilst aligning national policy with the supranational targets of the EU. Furthermore, France should seek more cooperation between various sectors to tap into the storage potential, especially focusing on hydrogen. The remaining recommendations focus on the coherency of France's energy policy and how investment is to be gathered.

## A.3. Stakeholder and country synthesis

Decision-making is a multi-faceted process, therfore, including the stakeholder landscape is key. Since not only stakeholders play a part in the decision-making, but also countries, both their current situations are explicated. Moreover, finding the focal issues of the stakeholders is useful to illustrate ideas that provide the necessary decision space (Ghanadan & Koomey, 2005).

Looking at the stakeholders, a few focal issues are found. First, the usage and debate around wind power are prevalent in the energy vision of many of the regarded stakeholders and countries. North Sea countries possess natural borders to the sea and thus possibility to deploy offshore wind power. Some member countries have to broaden their energy mix with wind power, whereas others need to be careful of the variability that it brings to the energy mix. However, a common issue found is resistance to wind power deployment, offshore and onshore. Other stakeholders have problems with offshore wind power. For example, fishermen lose their fishing grounds and oil & gas (O&G) stakeholders see a threat to their business case.

A second focal issue found by synthesizing the stakeholders is cost-effectiveness. Where the corporate stakeholder will already seek to have cost-effective businesses, the governments are lacking. The IEA recommendations for a lot of the discussed member states show that governments must incorporate the cost-effectiveness of sectors in their policies. Efficient use of the generation sources in the energy system should be a prerequisite for countries. This forms an important factor in shaping the energy system of the future.

Third, hydrogen is often mentioned as a niche technology most stakeholders ought to explore. Be it hydrogen storage, generation or hydrogen as a means of energy carrier for heat and fuels. The O&G stakeholders want to use parts of their existing infrastructure and make this suitable for hydrogen exploitation. Member states could use hydrogen to account for variability and to make the heating and transport sector more sustainable. The usage of hydrogen is therefore an important factor to take into account when regarding the future energy system configuration.

Last, the heat and transport sectors are lacking in meeting renewability targets amongst member states. Since sectors are coupled in the European energy system, renewing one sector will have an effect on other sectors. Therefore, it is important to regard all main supply technologies in the energy system and how they behave given that sectors are intertwined with one another.

# B

# Clustering methods

This appendix explicates the difference between the clustering methods using the Ward method and the complete method. The Ward method minimizes the variance in a cluster. Meaning data points with low variance amongst each other are deemed to be in the same cluster. The complete method maximizes the furthest distance between two data points that are not in the same cluster. This way, clusters are created that are as far away from each other in the decision space as possible. To test which algorithm is used, the same amount of clusters have been created. For this test 8 clusters are created, so a one-on-one comparison of the composition of the clusters can be drawn.

As can be seen from the four graphs underneath, the metric does not cause the composition of the clusters to change. Graph B.1 shows the precise same cluster composition as the graph of B.3. The same goes for the complete method graphs. What does make a difference is the method of clustering that is used. The types of clusters, as described in chapter 4.4 remain the same. That is, we see solar PV dominated clusters, wind dominated clusters, battery and wind dominated clusters, and balanced clusters wind solar PV, wind and transmission being prevalent. What does show is that with the complete method, the diversity of cluster types is larger. With the complete method we roughly see two solar PV dominated clusters, two balanced clusters, two battery and wind dominated clusters and two wind dominated clusters. In comparison, the Ward method yield just a single battery and wind dominated cluster type and three wind dominated clusters. This means that at a similar cluster amount, these algorithms cluster different SPORES together in a cluster. It also shows form the tables B.1, B.2, B.3 and B.4 that the Ward clusters contain precisely the same amount of SPORES and the complete clusters have precisely the same amount of SPORES. Since the complete method yields a larger variety of cluster types, i.e. not 3 wind dominated cluster and a single battery dominated cluster, the complete method is used in this study. It is however expected that results will not differ greatly, because the types of clusters created are similar, so the composition of the energy system configurations are all translated into four cluster types.

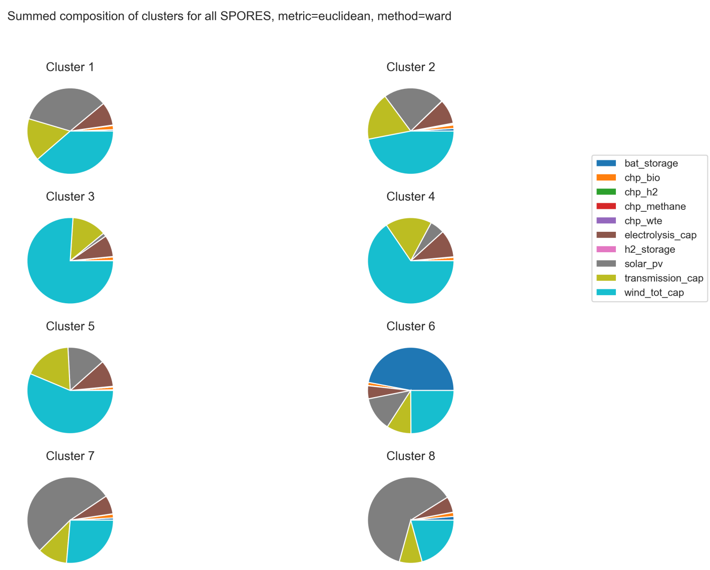


Figure B.1: Summed composition of clusters for all SPORES, metric=euclidean, method=ward.

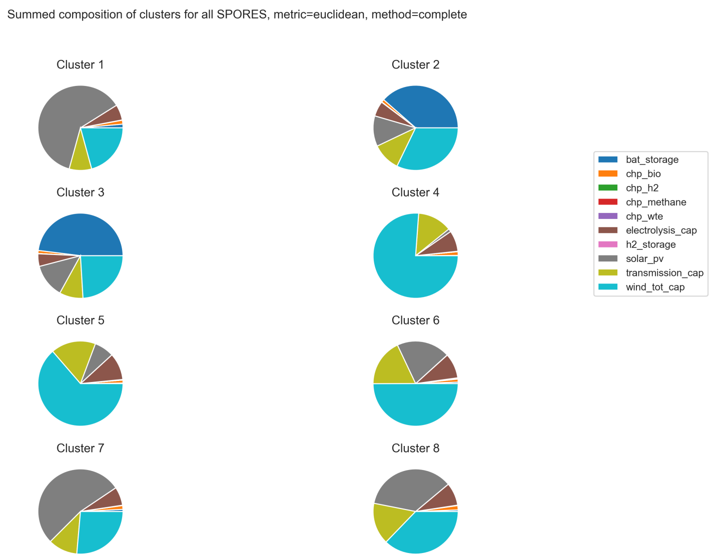


Figure B.2: Summed composition of clusters for all SPORES, metric=euclidean, method=complete.

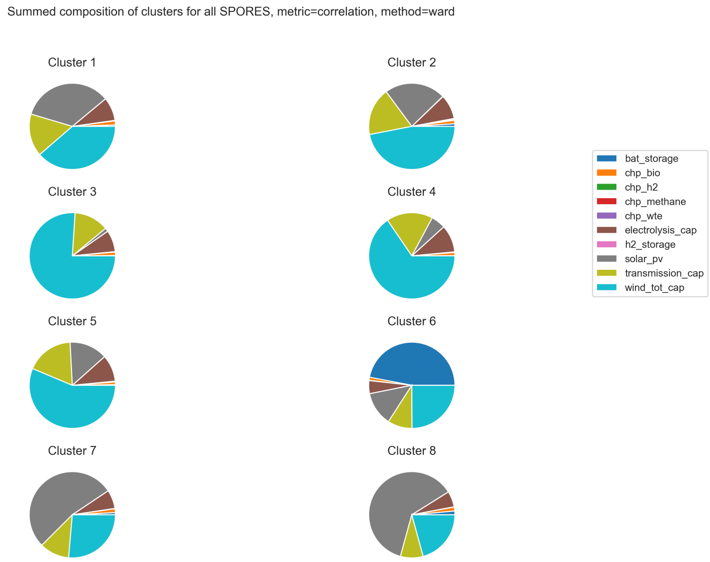


Figure B.3: Summed composition of clusters for all SPORES, metric=correlation, method=ward.

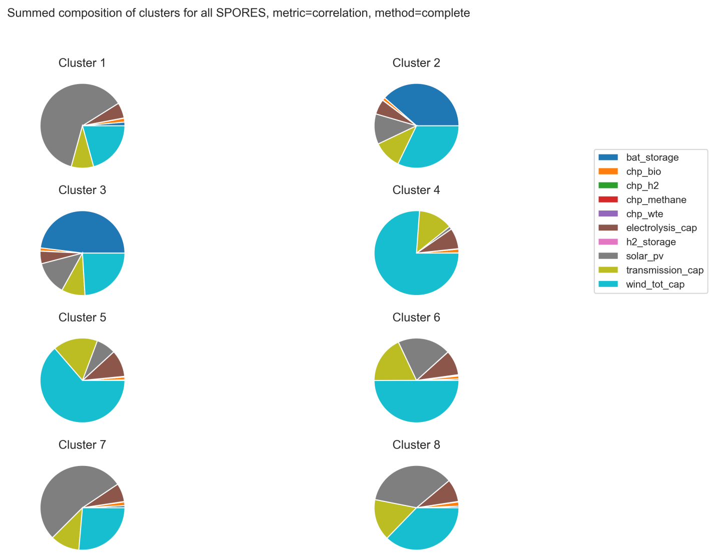


Figure B.4: Summed composition of clusters for all SPORES, metric=correlation, method=complete.

| **Cluster** | **#SPORES** |
|---|---|
| Cluster 1 | 63 |
| Cluster 2 | 105 |
| Cluster 3 | 44 |
| Cluster 4 | 101 |
| Cluster 5 | 242 |
| Cluster 6 | 21 |
| Cluster 7 | 6 |
| Cluster 8 | 18 |

Table B.1: Number of SPORES per cluster, metric=euclidean, method=ward.

| Cluster | #SPORES |
|---|---|
| Cluster 1 | 18 |
| Cluster 2 | 3 |
| Cluster 3 | 18 |
| Cluster 4 | 36 |
| Cluster 5 | 206 |
| Cluster 6 | 263 |
| Cluster 7 | 6 |
| Cluster 8 | 50 |

Table B.2: Number of SPORES per cluster, metric=euclidean, method=complete.

| Cluster | #SPORES |
|---|---|
| Cluster 1 | 63 |
| Cluster 2 | 105 |
| Cluster 3 | 44 |
| Cluster 4 | 101 |
| Cluster 5 | 242 |
| Cluster 6 | 21 |
| Cluster 7 | 6 |
| Cluster 8 | 18 |

Table B.3: Number of SPORES per cluster, metric=correlation, method=ward.

| Cluster | #SPORES |
|---|---|
| Cluster 1 | 18 |
| Cluster 2 | 3 |
| Cluster 3 | 18 |
| Cluster 4 | 36 |
| Cluster 5 | 206 |
| Cluster 6 | 263 |
| Cluster 7 | 6 |
| Cluster 8 | 50 |

Table B.4: Number of SPORES per cluster, metric=correlation, method=complete.

# C

# Appendix - Results

## C.1. Descritpive statistics of weather years and technologies

| | bat_storage | chp_bio | chp_h2 | chp_methane | chp_wte | electrolysis_cap | h2_storage | solar_pv | transmission_cap | wind_tot_cap |
|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 200.0 | 200.0 | 200.0 | 200.0 | 200.0 | 200.0 | 200.0 | 200.0 | 200.0 | 200.0 |
| **mean** | 1.146 | 0.447 | 0.006 | 0.032 | 0.049 | 2.838 | 0.006 | 5.448 | 4.826 | 17.164 |
| **median** | 0.003 | 0.426 | 0.000 | 0.001 | 0.046 | 2.698 | 0.000 | 3.194 | 4.555 | 16.652 |
| **std** | 5.666 | 0.216 | 0.017 | 0.084 | 0.015 | 0.586 | 0.019 | 6.824 | 1.004 | 3.350 |
| **min** | 0.000 | 0.025 | 0.000 | 0.000 | 0.037 | 2.083 | 0.000 | 0.002 | 3.228 | 10.272 |
| **max** | 35.317 | 0.987 | 0.077 | 0.427 | 0.124 | 8.119 | 0.078 | 40.685 | 8.800 | 27.491 |

Table C.1: Descriptive statistics for technologies of the weather year 2010 SPORES.

| | bat_storage | chp_bio | chp_h2 | chp_methane | chp_wte | electrolysis_cap | h2_storage | solar_pv | transmission_cap | wind_tot_cap |
|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 200.0 | 200.0 | 200.0 | 200.0 | 200.0 | 200.0 | 200.0 | 200.0 | 200.0 | 200.0 |
| **mean** | 1.127 | 0.294 | 0.007 | 0.024 | 0.054 | 2.703 | 0.007 | 6.394 | 5.029 | 13.854 |
| **median** | 0.007 | 0.234 | 0.000 | 0.000 | 0.052 | 2.550 | 0.000 | 4.588 | 4.560 | 13.508 |
| **std** | 5.224 | 0.186 | 0.021 | 0.066 | 0.014 | 0.560 | 0.021 | 6.323 | 1.327 | 2.672 |
| **min** | 0.000 | 0.030 | 0.000 | 0.000 | 0.044 | 2.095 | 0.000 | 0.001 | 3.230 | 8.571 |
| **max** | 31.379 | 0.824 | 0.077 | 0.415 | 0.111 | 7.345 | 0.076 | 36.581 | 9.032 | 22.370 |

Table C.2: Descriptive statistics for technologies of the weather year 2015 SPORES.

| | bat_storage | chp_bio | chp_h2 | chp_methane | chp_wte | electrolysis_cap | h2_storage | solar_pv | transmission_cap | wind_tot_cap |
|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 200.0 | 200.0 | 200.0 | 200.0 | 200.0 | 200.0 | 200.0 | 200.0 | 200.0 | 200.0 |
| **mean** | 1.180 | 0.372 | 0.007 | 0.028 | 0.061 | 2.564 | 0.006 | 5.535 | 4.588 | 14.699 |
| **median** | 0.062 | 0.327 | 0.000 | 0.001 | 0.058 | 2.352 | 0.000 | 3.040 | 4.361 | 14.067 |
| **std** | 5.355 | 0.234 | 0.020 | 0.073 | 0.016 | 0.631 | 0.019 | 6.627 | 0.889 | 2.924 |
| **min** | 0.000 | 0.000 | 0.000 | 0.000 | 0.046 | 1.953 | 0.000 | 0.001 | 3.060 | 8.362 |
| **max** | 32.452 | 0.994 | 0.080 | 0.312 | 0.125 | 7.650 | 0.069 | 39.004 | 7.116 | 23.952 |

Table C.3: Descriptive statistics for technologies of the weather year 2016 SPORES

## C.2. Decision space plots

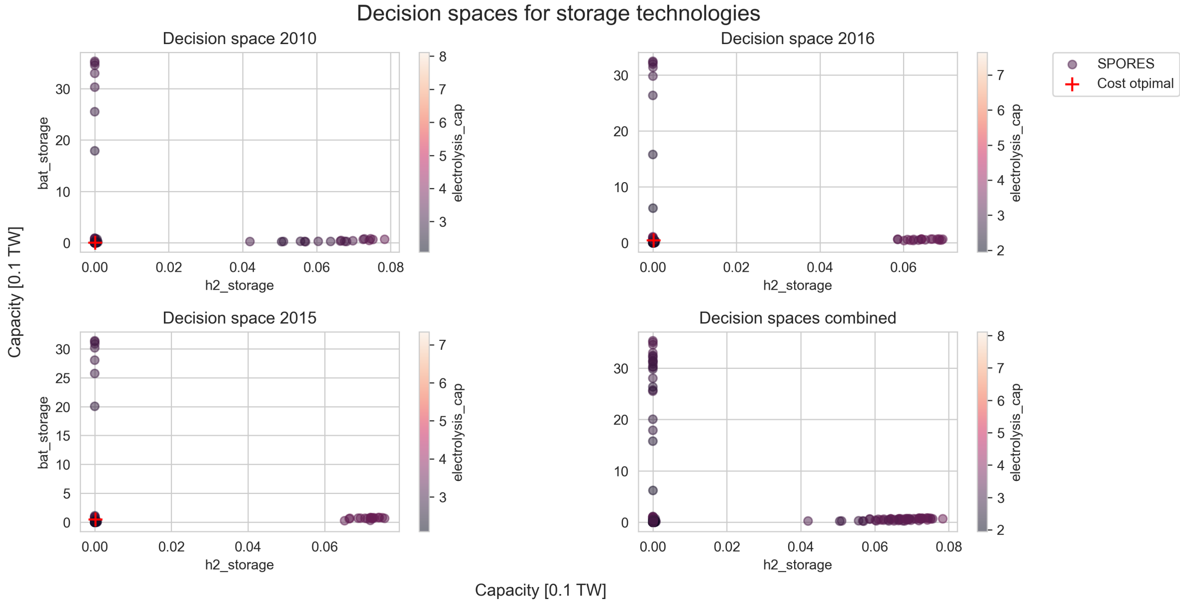


Figure C.1: Decision spaces per weather year and for all weather years combined for the storage capacities.

Figure C.1 shows the decision spaces for battery storage, hydrogen storage and electrolysis capacity. For the worst weather year, 2010, the upper bounds for hydrogen storage, battery storage and electrolysis is higher than the typical and best weather year. Moreover, for all the weather years the lowest capacity for hydrogen and battery storage is equal to 0, see also section 4.2. Additionally, for all decision spaces, it can be noted that battery and hydrogen storage stay close to the axis of the decision spaces. Meaning, that when battery storage is high, hydrogen storage is close to or equal to 0 and vice versa or both capacities are close to 0. For electrolysis, the installed capacity is mainly on the lower side, so little spread can be seen for this technology amongst the SPORES.

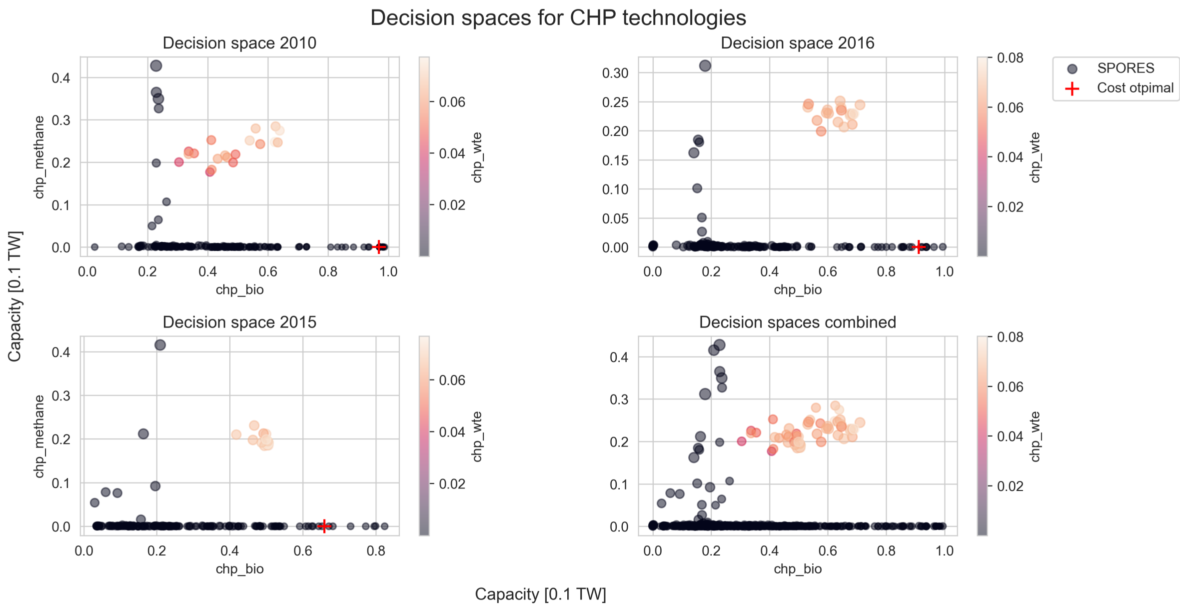


Figure C.2: Decision spaces per weather year and for all weather years combined for the CHP capacities.

Figure C.2 show the decision spaces for the CHP of biofuels, CHP of hydrogen (visualized by the size of the dots), CHP of methane and CHP of WTE installed capacities. With regards to CHP from biofuels, the lower bounds for 2010 and 2015 are close to 0, but only the lower bound of 2016 is 0 (see also table C.3). Moreover, 2016 has a lower upper bound for CHP from methane than the other two years. The upper bound for CHP from biofuels is the lowest for 2015. Looking at the upper bound of CHP from WTE, 2016 has a higher upper bound than the other two years. Additionally, it can be noted that when both CHP from methane and biofuels capacities increase, the CHP from WTE also increases (visualized by the colour shifting to yellow). The size of the dots, representing CHP from hydrogen, increases when CHP from methane increases. Lastly, the majority of configurations has low CHP from methane and WTE capacity and are highly spread for the CHP from biofuels capacity.

# C.3. Dendrogram all SPORES

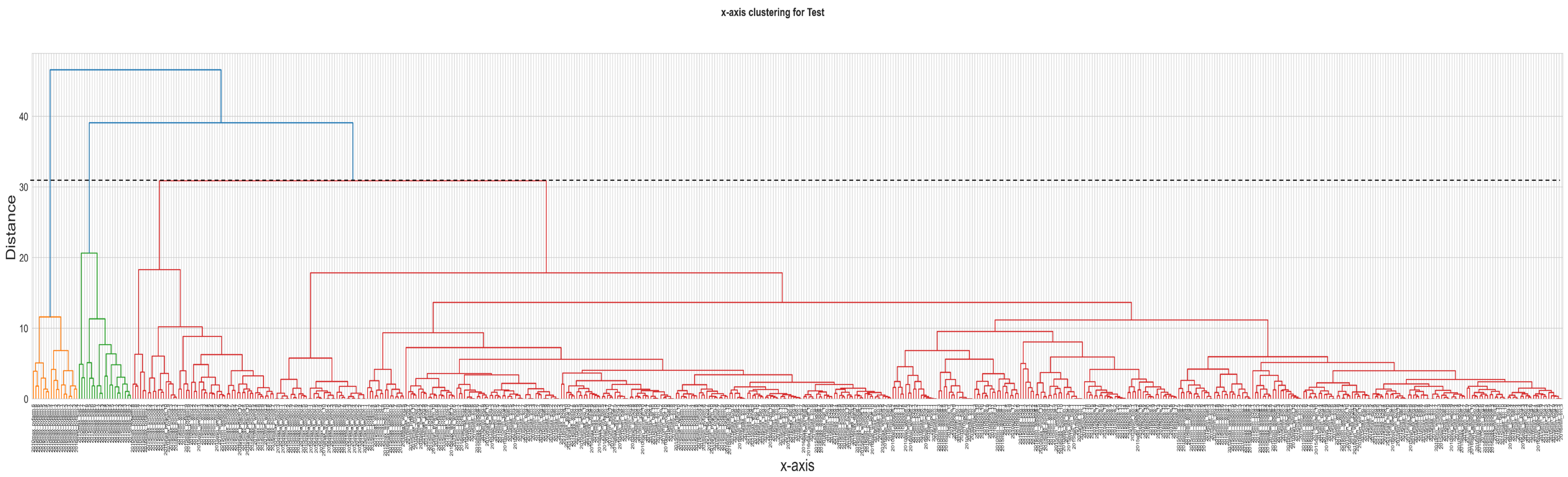


Figure C.3: Dendrogram for clustering all configurations

# C.4. Composition of clusters all SPORES

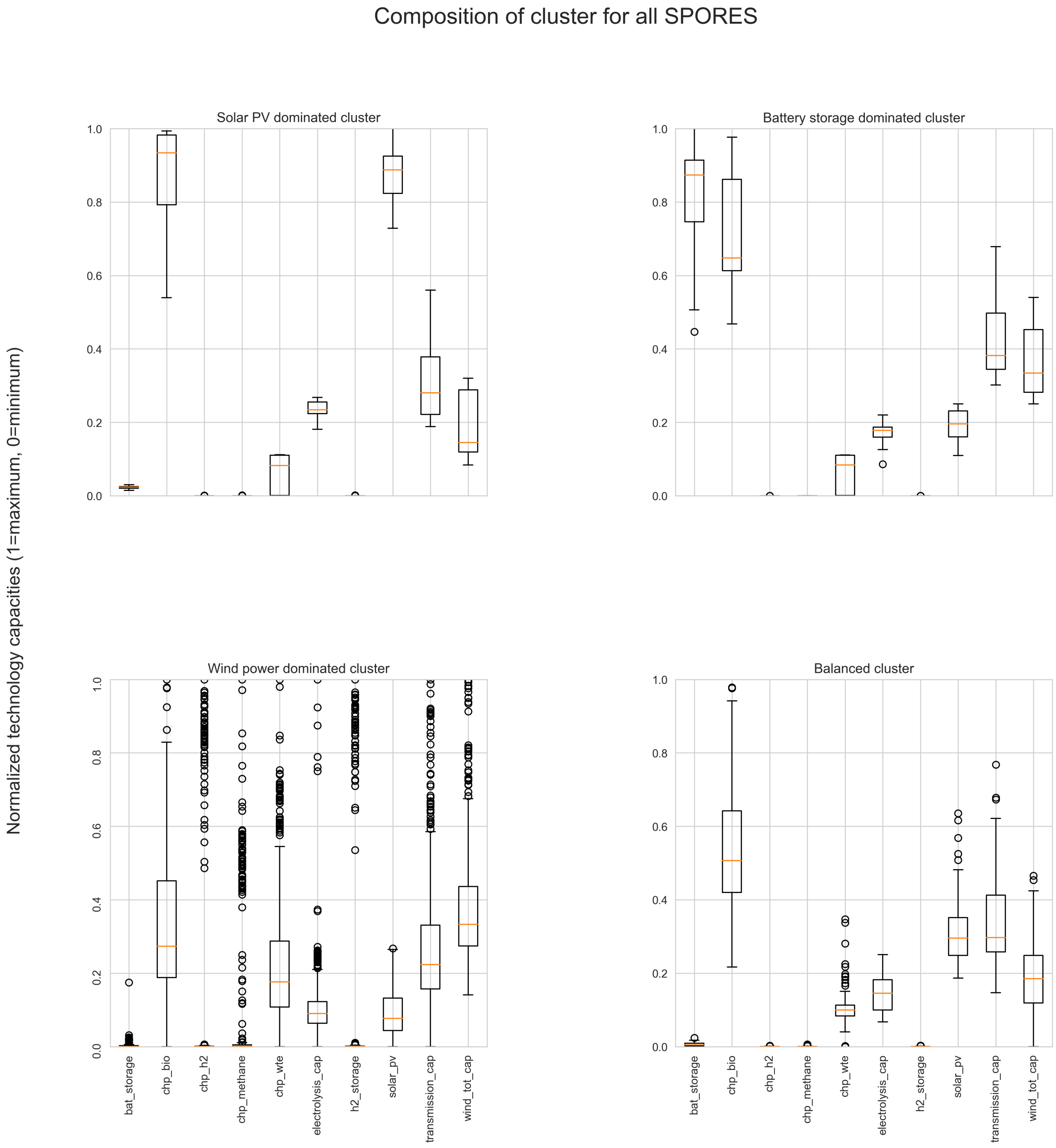


Figure C.4: Boxplots of the normalized (max=1, min=0) technology values per cluster for all SPORES.

# C.5. Dendrogram robust SPORES

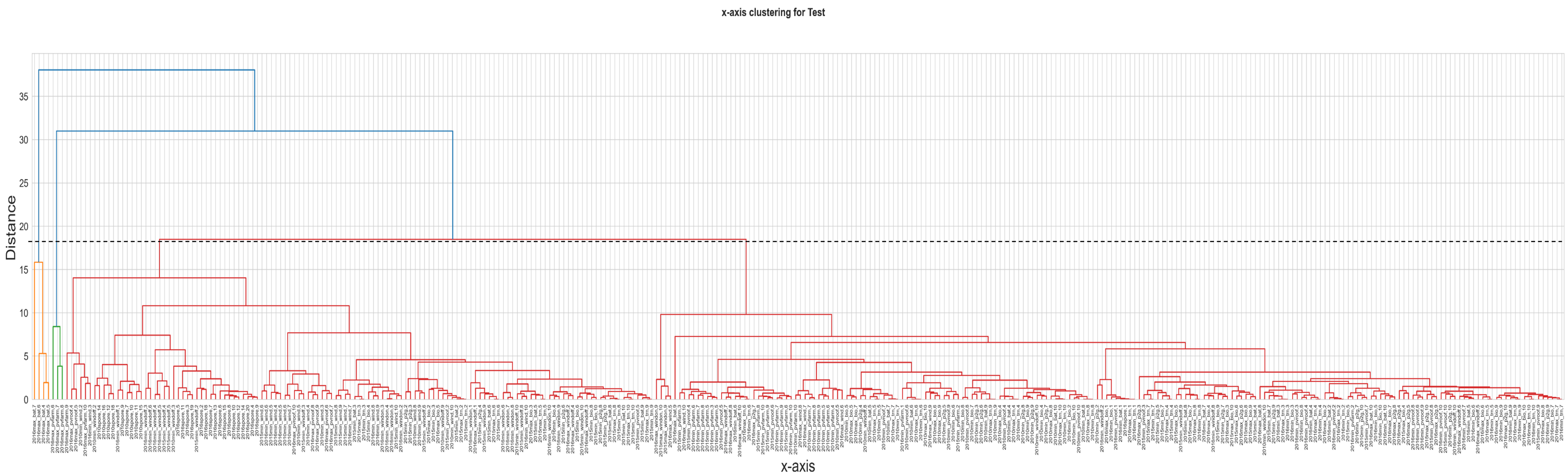


Figure C.5: Dendrogram for clustering robust SPORES.

## C.6. Composition of clusters robust SPORES

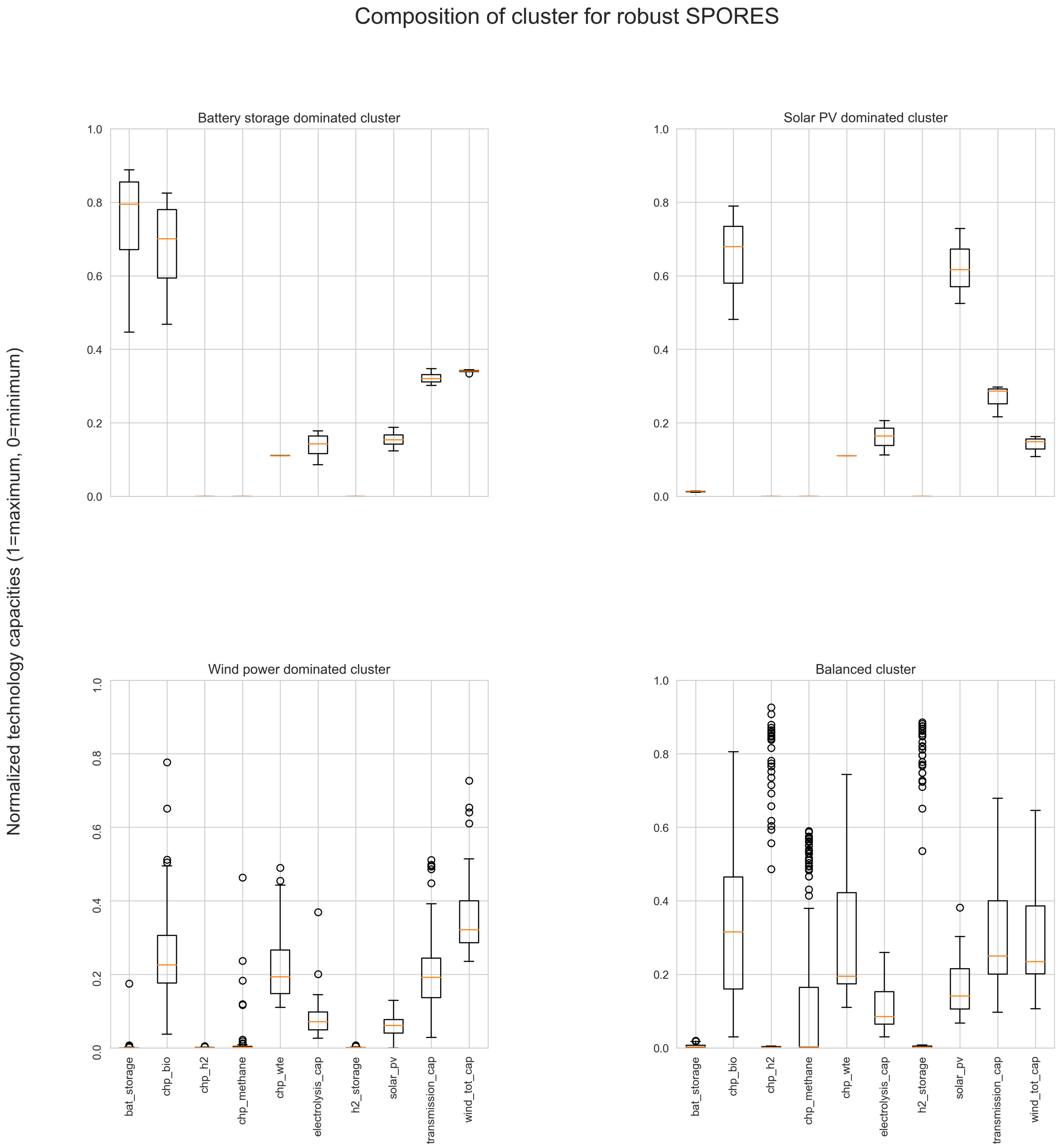


Figure C.6: Boxplots of the normalized (max=1, min=0) technology values per cluster for robust SPORES.

## C.7. Composition robust SPORES Pareto frontier

When regarding the names of the configurations in figure C.7 and C.8, it stands out that the majority of SPORES have “max_windoff”, “min_windon” or “min_wind” in their names. The “max_windoff” SPORES maximize offshore wind power capacity, with the first SPORES containing the highest share. The “min_windon” spores minimize onshore wind capacity, also with the first SPORES having the lowest amount of installed onshore wind capacity. Since wind deployment is high across these SPORES and offshore wind either is maximized or onshore wind is minimized, results show that the high-performing robust configurations contain a high share of offshore wind capacity. Looking at the configuration name it can also be noted that all high-performing robust configurations stem from the weather scenario year 2016, which is the typical weather scenario.

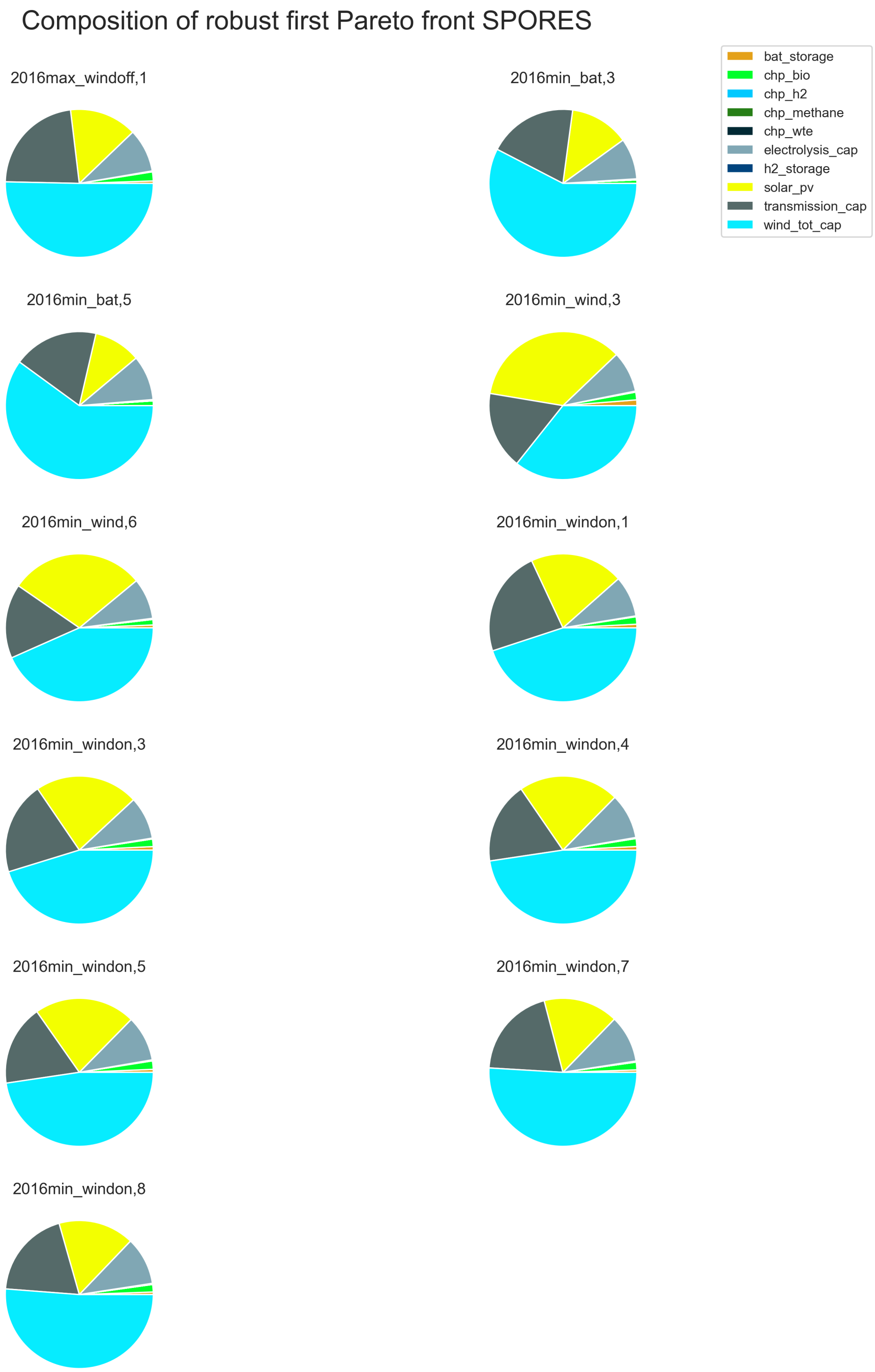


Figure C.7: Composition of robust configurations contained in the first Pareto frontier. Each color shows the capacity of a respective technology, a larger area indicated a higher capacity.

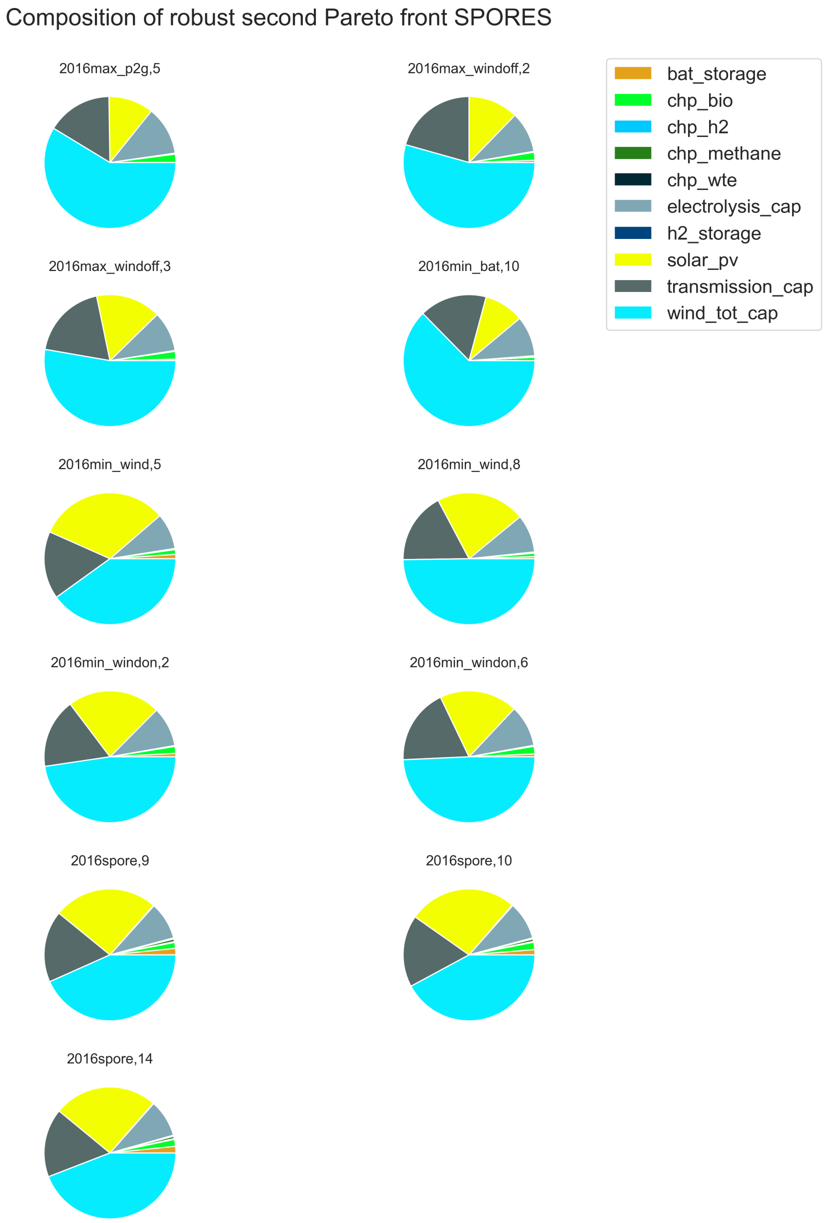


Figure C.8: Composition of robust configurations contained in the second Pareto frontier. Each color shows the capacity of a respective technology, a larger area indicated a higher capacity.

# C.8. Cluster core compositions with log scale

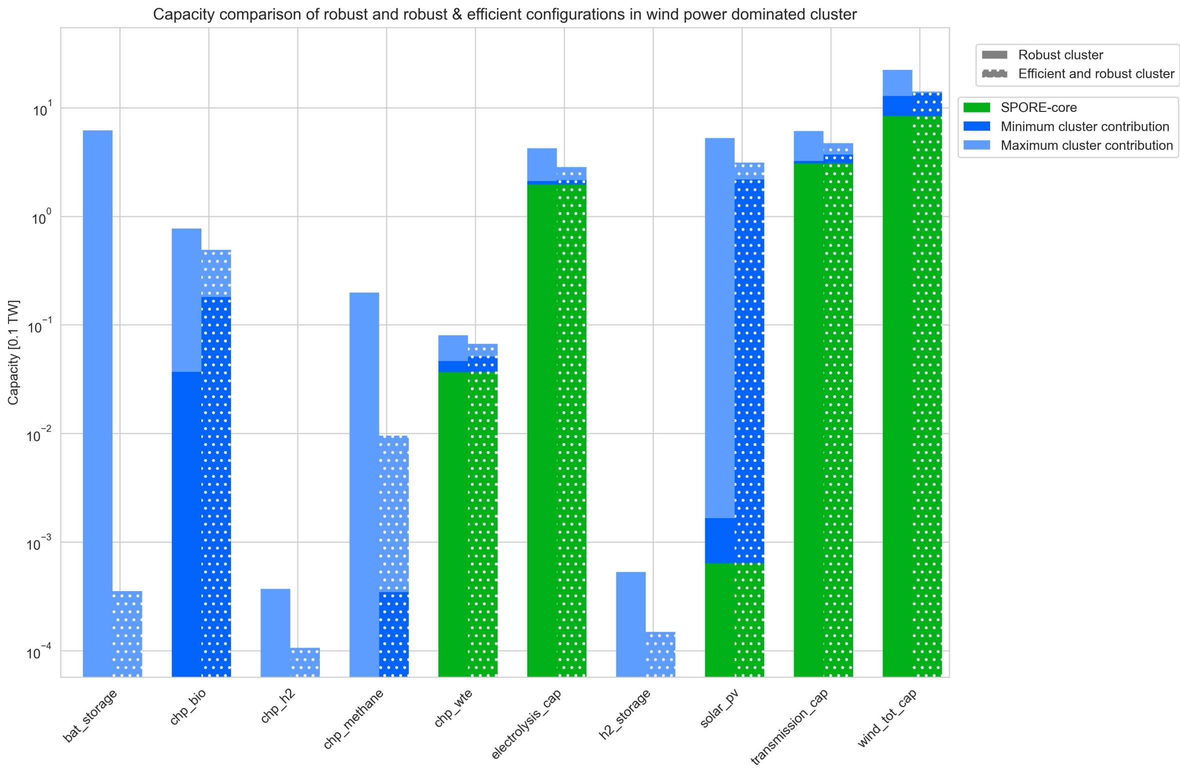


Figure C.9: Bar chart showing the common SPORE-core per technology with the minimum and maximum capacity of the robust wind power-dominated cluster. The left bars show the minimum and maximum values of the robust cluster per technology. The right bars show the minimum and maximum values of the high-performing configurations in the robust wind power-dominated cluster per technology. A dark blue bar means there is additional capacity needed on top of the common SPORE-core.

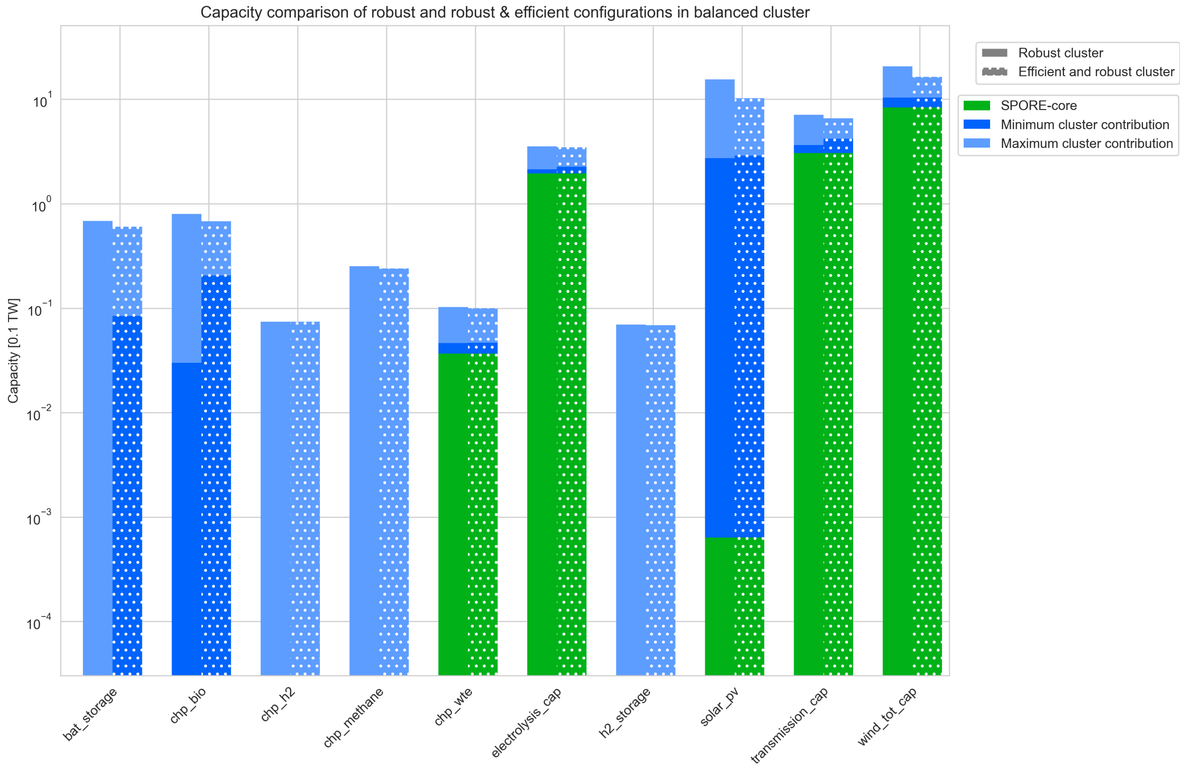


Figure C.10: Bar chart showing the common SPORE-core per technology with the minimum and maximum capacity of the robust balanced cluster. The left bars show the minimum and maximum values of the robust cluster per technology. The right bars show the minimum and maximum values of the high-performing configurations in the robust balanced cluster per technology. A dark blue bar means there is additional capacity needed on top of the common SPORE-core.