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Combining Parametric and Structural Uncertainty in Optimization Modelling for Sustainable Energy Systems.

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Preface

In the past 10 months, I had the opportunity to expand the knowledge of energy system modelling in cooperation with Witteveen + Bos and the Technical University of Delft. It was the biggest solo project of my study career, resulting in many challenges and lessons learnt along the way. For Witteveen + Bos, Samuel has been my daily supervisor. He helped me with almost everything I needed for my thesis to be of sufficient quality through both the companies' eyes, as well as the TU's. The weekly meetings and the urge to create my own deadlines kept me on track and focused on the important aspects. Samuel, thank you for being the perfect support for my thesis and thank you for helping me find my way within W+B.

As most TU Delft supervision candidates with the perfect background were too occupied with other work, finding proper supervision in this subject was hard in the beginning of my thesis. Luckily, Wiebren and Lindert were there to accept me as their thesis student and help me get started nonetheless. About 2 months in, Francesco started his new job at the University of Delft, providing the perfect expertise to help me shape my thesis research. Francesco allowed me to use his baby (read the SPOREs method) and try and improve parts of it with this thesis. Francesco, thank you for providing in depth value to the research and thank you for helping me find ways to move forward with it when I was stuck. Wiebren and Lindert, thank you for explaining and maintaining the right process steps in this thesis and thank you for your excellent supervision.

In general I want to thank my MSC friends, first rowing team, heavyweight rowing team, compo-acht team, Swiss friends and BEP group for providing me with the necessary distractions and good times during the weekends and evenings. I want to thank Alec, Mike and Vincent for providing tips and guidelines on how to go about doing a thesis in general. A big thank you to Jan and Mitchel for providing feedback on my report content, and Willemijn for helping out big time with the report layout and design. I am grateful for my parents, stepparents, the in laws and siblings for their indefinite support during my studies. And last but not least, I want to thank Lotte for being my infinite well of support and life jacket during the challenging times and for being critical when it was most necessary.

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Abstract

The swift reduction of human's carbon footprint is essential to prevent irreversible damage to the climate and to meet climate policy targets. Designing flexible and reliable future energy systems is a big contributor to meeting these goals. While energy system models have improved in the last few decades, they remain vulnerable against parametric and structural uncertainty due to the varying characteristics of parameters and the hardship of modelling all constraints and drivers accurately. This thesis proposes a method that addresses both uncertainty types in energy system modelling by applying SPORES cost optimisation and Monte Carlo scenario modelling simultaneously.

The main case study uses 27 input scenarios with varying outcomes for grid electricity price, solar yield and energy consumption to provide insight in a 100 household neighbourhood energy system with heating, cooling, electricity and hydrogen as energy carriers. With 1377 (near-)optimal solutions, a novel approach in analysis and post processing is used to provide 52 useful configuration options that each have their strengths and weaknesses to different political, economical, social and technical drivers. These configurations are tested for cost, security of supply, CO_2 emissions and grid dependency. Those results are visualised through ridge plots and statistical tables to provide a clear overview between each configuration's trade-offs. An example is included to show how those results can be used for improving energy system design in practice.

This thesis shows that two methods can successfully be combined into one universal one, while providing valuable design insights for energy systems under uncertainty. Furthermore, this method can be applied to a wide variety of energy systems, as long as its possible components, their technical aspects and their allowed interactions are known beforehand. As many future energy system aspects are uncertain, it should be seen as a vital tool to help speed up the decarbonization.

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1 Introduction

This chapter, in sections 1.1, 1.2, and 1.3, background information substantiating the research questions (section 1.4) and the general scope is provided. Section 1.1 explains the necessity for a sustainable energy transition and the relevance of energy system modelling (ESM). In section 1.2, the two main ESM approaches "simulation" and "optimization" are elaborated. In section 1.3, parametric and structural uncertainty are addressed further and the difference between stochastic and deterministic parameters within ESMs is explained. Section 1.4 entails the research questions and section 1.5 the report structure.

1.1 Transition Necessity and Energy System Modelling

Over the last 800000 years, the carbon dioxide (CO_2) concentration in the earth's atmosphere has never reached higher concentration than 300 parts per million (ppm) until around 1910 [14] [15]. The annual concentration of CO_2 particles has only increased since then [1]. The significant increase in CO_2 concentration is strongly correlated to the human population increase [16], and the resulting increase in fossil fuel combustion [17] to meet its growing energy demand [18]. CO_2 is one of the greenhouse gases that contribute to temperature increase in the earth's atmosphere. Heat is prevented to leave the earth's atmosphere, due to CO_2's capacity to absorb radiative heat [19]. The rising temperature contributes to an increased ocean and air temperature, increased frequency of extreme weather events (heat waves, drought, heavy precipitation and flooding due to higher sea levels), loss of ecosystems and an increased risk of endangering food production systems, human health, and tourism [20] [21]. Reducing human's footprint and transitioning to a more sustainable society is therefore essential to reduce those risks.

Transitioning to a more sustainable society is complex due to a large amount and wide variation of relevant actors and interests. Such a transition is substantiated by aspects in economic geography, science innovation, organisational strategy, sociology, and modelling [22]. The engineering consultancy company Witteveen + Bos (*W+B*) aims to support this sustainable transition by executing more than 3000 projects annually in the fields of water, infrastructure, environment, and construction. By doing so, goals of sustainable development are central in executing these projects [23]. Many of these project's hinge on the development of energy systems that need to be reliable and flexible in design due to uncertain aspects of future energy system behaviour.

Energy system design is evolving over time as well because of the changing scope of future energy systems. With the changing political agendas and the rise of cheaper and more efficient (sustainable) technologies, new challenges come to light. Energy production will become heavily dependent on unpredictable weather due to the increasing share in solar and wind [24] [25] [26]. Moreover, the desire to be self-sustainable or energy neutral on a decentralised scale is increasing. Meaning that choices of a single actor, can influence the systems' behaviour more radically than in larger scaled energy systems. Furthermore, economical aspects of future technologies are different. In the past, over-sizing a diesel generator (capital expenditures, CAPEX) did not have large

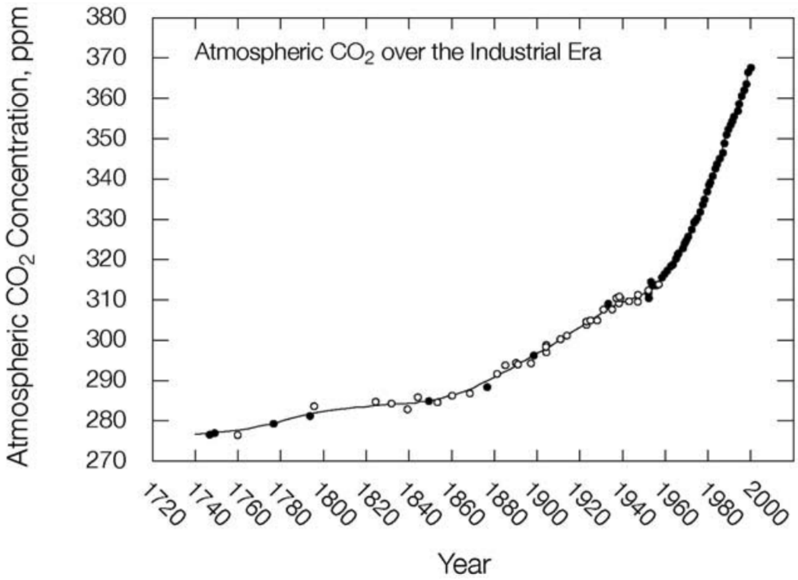

Figure 1.1: Atmospheric CO_2 concentration during the industrial era. A steep increase in concentration is visible between 1960 and 2000. Source: Keeling et al [1].

consequences for the total system costs as most costs resulted from purchasing fuel (operating expenditures, OPEX). With emerging technologies like wind and solar, the sizing defines most of the costs since there is as good as no fuel cost. Additionally, under-sizing or over-sizing might even result in an energy system not being feasible or being much more expensive than required. All these uncertainties implore the need for methods that can calculate these aspects and their consequences beforehand to decide on the best design.

Going about designing energy systems with aspects on this level of complexity requires a more sophisticated design approach. The design of such energy systems relies more and more on the use of models [27] [28]. An ESM includes all the components and their interactions, that are required for the generation, conversion, transmission, and consumption of energy within a specified energy system working area [29]. ESMs provide scientific, financial, industrial, and political insights through the computational combination of engineering, economic and environmental perspectives [30] [31]. These insights are used to help plan, design, and implement said energy systems in society. According to literature, modelling of energy systems is applied in different levels of variable types, theoretical substantiation, technological depth, timescales, spatial scales, and model purposes [32]. This substantiates that energy system modelling is applied in many forms.

1.2 Energy System Modelling: Simulation and Optimization

Two general ESM approaches are distinguished: simulation and optimization [33], with each their benefits to improve energy system design. Optimization finds an optimal energy system design configuration for a chosen objective function such as minimising cost, CO_2 emissions or energy use [34]. Despite being heavily dependent on the correct interpretation and representation of component behaviour and inputs for reliable results, optimization is a very strong tool to finding cost-effective design. In general, optimization models suffer a heavier computational burden than simulation models [33].

Simulation focuses on analysing the performance of an energy system design for certain scenarios in which key parameters are modified. With simulation models, the user oversees making the crucial decisions in defining these different scenarios. While in optimization the crucial segment is defining the system component behaviour. In the simulation approach, both high scoring and bad scoring scenarios are analysed, whereas in optimization, only the best solution is considered. Therefore, the reasons why sub-optimal solutions operate worse are not discovered in optimization, while this behaviour can be found and understood by comparing those scenarios in simulation. Optimization techniques are “blind” for non-optimal options, and must be modified by hand to see alternative near-optimal structurally different solutions [33].

Table 1.1: Aspects of Simulation and Optimization.

	Simulation	**Optimization**
Definition	Model that tests the performance of a system configuration for certain user-defined scenarios.	Model that solves for an optimal system configuration by an objective function with system restraints.
Model output	Performance of system for given scenarios.	Optimal system configuration for given objective function.
Computational burden	Low	High
Human error	In defining the scenarios to test the system on.	In Defining the model relations, behavior, and model inputs.
Benefit	Can understand the sensitivity of decision variables by comparing different scenarios.	Ability to determine competitive, cost-effective solutions in a quantitative way without emotions.
Downside	Scenarios are defined by user and are likely sub-optimal and too dependent on user expertise to define reliant/ relevant scenarios.	Cannot look past the optimal solution and does not directly understand which decision variables have more influence.

Cost-effective optimal designs have to be identified and used in order to provide competitive, long-term energy system solutions in modern ESM that can provoke the energy transition. These energy system optimization models (ESOM) have been extensively applied to provide essential insights on all scales, proving optimization models to be crucial for energy system design [35]. However, the loss of resolution in the solution space of optimization methods is not desired since future uncertainties in the energy system are imminent. The preferred ESM technique is essentially one that can combine the benefits of optimization and simulation modelling and can find optimal solutions, while preserving the flexibility to design in structurally different ways to cope with future uncertainties. In some cases, the strengths of both optimization and simulation models are already combined in a single model [36, 37, 38, 39] [36] [37] [38] [39]. Nonetheless, in these cases a concise approach that can summarise and analyse the results in a structured manner still lacks.

1.3 Energy System Modelling and Uncertainty

Addressing uncertainty is an important aspect within ESM [40]. Literature [29] [41] defines 2 kinds of uncertainty, namely parametric and structural. Parametric uncertainty is the result of misrepresenting parameters in a model due to a lack of knowledge about them (like weather data, demand forecasts and fluctuating prices). Structural uncertainty is the discrepancy that results from the equations and interactions that define a model compared to the real system (like unmodelled objective functions and unmodelled constraints). Both types of uncertainties are an important challenge within ESOMs. Parametric uncertainty is often high as many future parameters are not perfectly predictable beforehand and can therefore not be modelled in full confidence. Structural uncertainty is often high as ESOMs only solve for a chosen objective function (usually minimise cost or CO_2 emissions), thereby ignoring other decision drivers like political, cultural, and normative aspects [42]. This uncertainty type can be addressed by finding structurally different solutions near the optimal solution that can satisfy objectives other than just economically optimal ones [43].

Parameters are represented in either a deterministic or stochastic manner within ESM. In the deterministic approach, all parameter behaviour and values are known (or assumed) perfectly by working with expected values. In the stochastic approach, randomness is included in the system by either representing the parameters in a stochastic distribution or by modelling a representative number of samples from it. The stochastic optimization technique greatly outperforms the deterministic one, when considering uncertainties in long-term future energy system design [44]. The deterministic approach is more suited for design scenarios with current or expected information [45], and less suitable for complicated many sided scenarios with built-in uncertainties [46].

When designing energy systems for future long-term applications, designers should consider a several features of uncertainty, well described by [47] in three aspects of *"deep uncertainty"*.

- The interactions of the essential driving forces in the long-term future are unknown beforehand.
- The way to represent vital uncertain parameters in the most realistic mathematical manner is never perfectly representable.
- One of the non-optimal alternatives may provide a more suitable solution for certain problems than the optimal solution.

A literature review [42] is conducted on how these aspects of uncertainty are systematically assessed in 34 different ESOMs. Subsequently, four techniques to apply uncertainty to ESOMs are identified, Monte Carlo Analysis (MCA), Robust Optimization (RO), Stochastic Programming (SP), and Modelling to Generate Alternatives (MGA). While MCA, RO and SP can only address parametric uncertainty, MGA provides the ability to take on structural uncertainty. Other ordinary methods to decrease the structural uncertainty are increasing complexity to improve model dynamics, involving expert opinion to define the model behaviour and model comparison. Chapter 2.2 and 2.3 address the relevant and available approaches that can tackle parametric and structural uncertainty and how they operate. It should be mentioned that there is not one best approach when including uncertainty. Therefore, the choice of approach should always depend on the desired type of insight results, the accessibility of data, and the relevant area of uncertainty [42].

Unfortunately, the complexity and computational burden of an ESM increases when any type of uncertainty is included [45]. Despite approaching more accurate and representative results, this still remains a problem for especially large scale models [48]. The manner of complexity of an energy system is established by the designer. Therefore, the trade-off between complexity, accuracy of results and computational power is important when designing computational ESMs and should always be considered when choosing the model configurations. Eventually, the added accuracy decreases with added complexity, meaning that increasing complexity does not add marginal value to the added accuracy at a certain point [49].

Although various methods are available to take on each type of mentioned uncertainty, there is a deficit in literature where both are applied simultaneously [50] [51], let alone in a systematic way. There is need for a systematic approach that includes parametric and structural uncertainty, to improve future cost-effective intermittent energy system design [52] [53] [13]. Hence, the goal of this thesis is to reduce that knowledge gap by providing such an approach.

1.4 Research Questions and General Scope

Now that basic background information is provided, the thesis objectives and research questions are addressed. The purpose of this thesis is twofold. Firstly, this thesis creates a method addressing parametric and structural uncertainty to add new scientific value to the energy system modelling field. Secondly, this thesis aims to provide the company W+B with relevant and useful insights that can improve their case designs, as this thesis takes place in collaboration with W+B. These purposes are represented by the main research question:

How can intermittent energy system models provide reliable insights for optimized energy system designs by systematically including both structural and parametric uncertainties?

The main research question can be split up into several sub research questions that help answer the main research question.

1. Which variables are most relevant to model as uncertain in the ESM?

2. How can these uncertain variables be modelled in a reliable and accurate way to be used as inputs for the combined method?
3. Which methods are effective in addressing parametric and structural uncertainty in ESOM and which ones are most suitable for this thesis?
4. How can the most suitable methods be systematically combined into a single method?
5. Can applying the method to one or two intermittent and renewable case studies (im)prove its effectiveness and does it improve energy system design?
6. What kind of useful insights can this method provide when applied to one or two W+B cases regarding effective energy system design?
7. How can the method be made easily accessible for other future energy system design projects?

1.4.1 Motivation of the Research Questions

For any parametric uncertainty approach to work well, the representation of the uncertain variables must be adequate for the model to produce good results (2). Furthermore, only the most relevant uncertain variables for the case study must be established (1). Expertise and accurate methods must be formulated and used to create trustworthy variables that represent the plausible future (3). Both types of uncertainty are to be applied at once to provide a new scientific approach (4).

The method will be applied to two case studies to test its performance. One of these case studies is based on a currently ongoing project of the company W+B. Both case studies are related to sustainable energy system design and take place on a relatively small scale (non-national) (5). An underlying goal of this thesis objective is to provide W+B with useful design guidelines and insights for of their case projects (6). The method can be compared to a basic design approach to determine if it provides useful insights.

Since energy system design methods can still be improved by including uncertainty more thoroughly in the design process, it is desired to make the method (when proven useful) accessible and applicable for other similar projects as well (7) [54].

The general scope of this thesis is not focused on the optimization of existing energy systems but on future systems that still have to be designed, as these methods are designed for it and since W+B wants to apply it for their future design cases. It aims to combine parametric and systematic uncertainty in an atomised manner and will be applied to two case studies to test and validate its effectiveness. After the thesis background is provided at the end of chapter 2, the complete thesis scope will be defined in more detail.

1.5 Thesis Structure

In the method chapter 2, the fundamentals of optimization and several available ESM methods and frameworks with their benefits and disadvantages are researched. Subsequently, uncertain variables and their role within ESMs are discussed. The scope of this thesis is found at the end of chapter 2. In chapter 3, the method that is be applied for this thesis is elaborated, followed by the case studies. The results come forward in chapter 4 and the discussion, future research, and recommendations in chapter 5. In chapter 6, conclusions of this work are drawn.

2 Theoretical Background

This chapter provides details on the available methods to complement the thesis objectives and to elaborate on how the chosen methods are applied. Therefore, this chapter covers the remainder of the literature research. First off, the optimization methodology and possible applications are discussed in section 2.1, followed by methods that can address structural and parametric uncertainty within energy system models in sections 2.2 and 2.3. Subsequently, available optimization frameworks are discussed in section 2.4, followed by how uncertain variables can be portrayed in ESM, and on what choices the selection of them should depend on in section 2.5.

2.1 Optimization

There are many ways to apply optimization in ESM. In this section, the general methodology of optimization is explained by elaborating on a simple dispatch optimization problem. Afterwards, relevant types of optimization found in literature are highlighted.

2.1.1 Optimization Methodology with Example

Energy system optimization models are applied for this thesis due to its widely accepted effectiveness in providing insights in ESM [55]. Optimization itself comes in many forms, but linear optimization is used as an explanatory case in this section to understand how it operates. As briefly touched upon in chapter 1.2, the goal of optimization is to either minimise or maximise an objective function by changing the values of the decision variables that are subject to constraints. Any optimization problem therefore consists of 3 components:

1. Objective function: The problem function, subject to the decision variables'values (2.1).
2. Decision variables x_n: The variables that need to be optimised for the optimal solution.
3. Constraints: The restrictions to which the decision variables are subject to (equation 2.2).

In the context of ESOMs, these objective functions can be minimising cost, minimising CO_2 emissions, minimising energy usage, or maximising profits. Basically, any objective that can test an energy system for it's effectiveness [56]. The decision variables are resources that contribute to this objective function. These decision variables are limited by constraints, meaning that they cannot just take any value because of physical or technical properties. These constraints can be maxima, minima or binding (equal to). Within LO, any objective function $f(x_n)$ is subject to only linear relations c_n, and linear decision variables x_n, meaning that all decision variables have the power of one (see equation 2.1).

$$\text{Objective function: } \textit{Minimize}\, f(\mathrm{x}_n) = \mathrm{c}_1 * \mathrm{x}_1 + \mathrm{c}_2 * \mathrm{x}_2 + \cdots \mathrm{c}_n * \mathrm{x}_n \tag{2.1}$$

$$\begin{aligned} \textit{S. t. constraints: } a_{11} * x_1 + a_{12} * x_2 + \cdots a_{1n} * x_n &\leq b_1 \\ a_{21} * x_1 + a_{22} * x_2 + \cdots a_{2n} * x_n &\leq b_2 \\ &\vdots \\ a_{m1} * x_1 + a_{m2} * x_2 + \cdots a_{mn} * x_n &\leq b_m \end{aligned} \tag{2.2}$$

Where c_n represents the relation between the objective function value per unit of decision variable x_n and where a_{mn} is the variable that represents the relation between the constraint and decision variable.

When the objective function, all relevant constraints and the decision variables are defined, the optimization problem can be solved. This can be done analytically or by using a solver. When using a solver, it iterates over different configurations of decision variables until an optimal solution is found. For non-linear optimization, the solvers are required to be strategically efficient to select the global optimum from multiple local optima [57] [58] [59] [56]. In the next section, different approaches to find the global optimum are addressed, and in section 2.4, different applicable solvers and their advantages are discussed.

When applying LO to a basic energy system problem example, an objective function can be to minimise the total cost function $C(c_n, x_n)$ [$] of operational capacities x_1 and x_2 [MW] of two energy plants. Each plant has different marginal operating costs of c_1=30 [$/MW] and c_2=40 [$/MW] and each plant has a maximum operation capacity b_1=50 [MW] and b_2=70 [MW]. The total operational capacity of both plants must meet a total demand of b_3=100 [MW]. For this example, the LO problem is visualised in figure 2.1, and works by using equation 2.3:

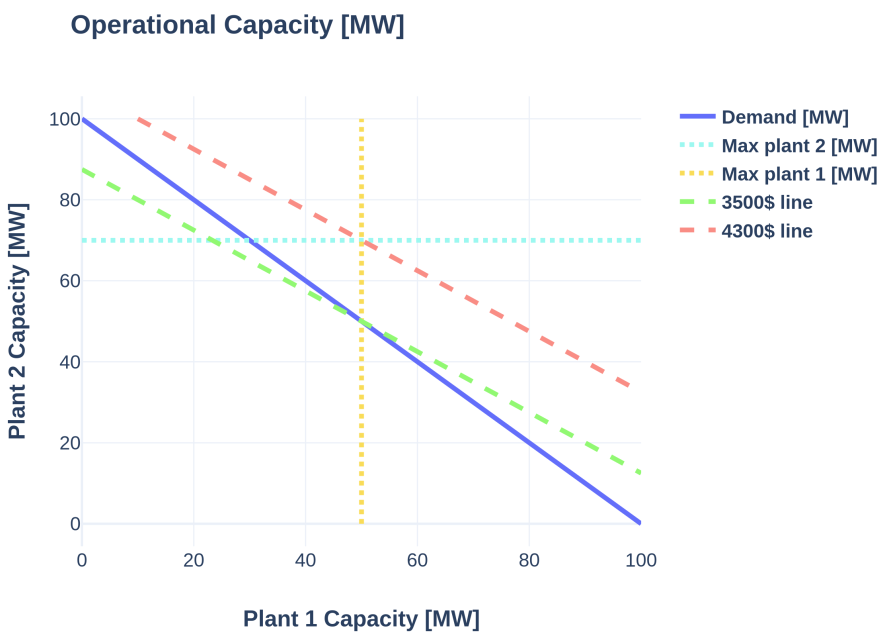

Figure 2.1: The constraint lines of a simple optimization problem.

$$\begin{aligned} \text{Objective function: } \textit{Minimise } C(c_n, x_n) &= 30 * x_1 + 40 * x_2 \\ \textit{S. t. constraints: } 1 * x_1 &\leq 50 \\ 1 * x_2 &\leq 70 \\ x_1 + x_2 &= 100 \\ \text{Optimal Solution: } x_1 &= 50 \\ x_2 &= 50 \\ \text{Total cost } &= 30 * 50 + 40 * 50 = 3500\$ \end{aligned} \tag{2.3}$$

For most optimization problems, the optimal solution is directly determined by some of the constraints. Those constraints are called "active" constraints. In the example, the optimal solution is determined by 2 active constraints. These 2 active constraints are the maximum operational capacity of energy plant 1 (b_1) and the demand constraint. When either one of these constraints is changed by 1 unit, the optimal solution will also change. For the maximum operational capacity of plant 2 (b_2), changing its value by 1 unit will not change the optimal solution. Therefore, it is a non-active constraint for this particular system.

2.1.2 Optimization Types

Linear optimization or linear programming (LP) is not the only optimization type that is being used within ESM. There are also optimization problems with non-linear constraints and objective functions (NLP). This is often the case for more complex models, where relations cannot be represented in a linear manner. This results in more than one extreme value and thus multiple local optimal solutions. Problems with more than one local optimum are called non-convex. Within optimization problems, decision variables can also be limited to discrete values. These decision variables can only take on integer values in this context. These optimization problems are called (Mixed) Integer (non) Linear Programming ((M)I(N)LP). Mixed programming occurs when the decision variables can take either integer or continuous values. An overview of the optimization problem classes, as defined by [2] can be seen in figure 2.2.

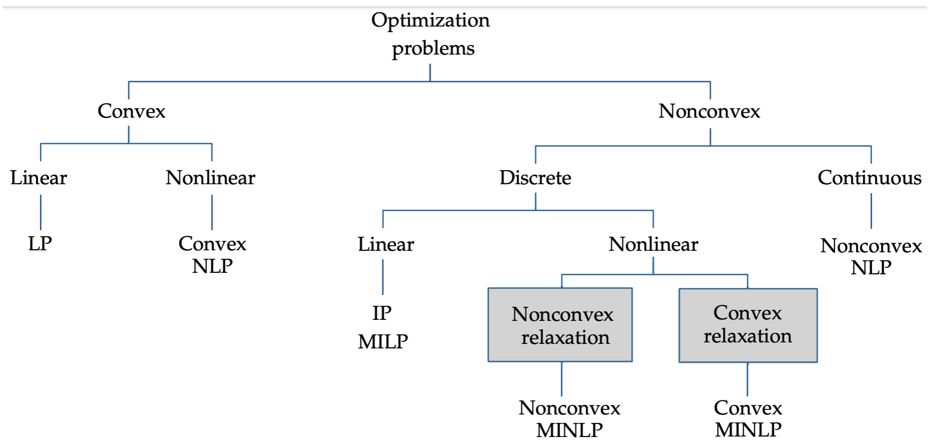

Figure 2.2: Optimization problem classes. Source: Lin et al [2].

Several literature reviews have been conducted on how optimization is applied to ESM [10] [11] [12] [2]. In these reviews, different classifications have been used to differentiate between the different methods. The most relevant and notable optimization methods are highlighted in table 2.1.

Uncertain optimization is most relevant for this thesis. The selected parametric uncertain optimization technique (MCS/MCA) as well as the selected structural uncertainty technique (SPOREs), are explained more intensively below in section 2.2 and 2.3. A more elaborate explanation of the other optimization techniques that can address uncertainty can be found in Appendix B. Other techniques that are less relevant for this thesis and not used, are shortly addressed below (table 2.1).

Table 2.1: Optimization types in literature [10] [11] [12] [2] [13].

Optimization type
Optimization problem types: - Linear Programming (LO/LP) - Non-linear Programming (NLP) - (Mixed) Integer (non) Linear Programming ((M)I(N)LP)
Uncertain Optimization: - Stochastic Optimization (SP/SO) - Multi-Stage Optimization (MSO) - Robust Optimization (RO) - Monte Carlo Simulation (MCS) - Chance-Constraint Method (CCP) - Risk Averse Optimization (RVA) **Artificial Intelligence Optimization:** - Genetic Algorithm (GA) - Particle Swarm (PS) - Simulated Annealing (SA) - Artificial Neural Network (ANN) - Ant Colony Optimization (ACO) **Other:** - Dynamic Programming (DP) - Multi Objective Optimization (MOO) - Multi Agent Approach (MAA) - Modeling to Generate Alternatives (MGA) - Spatially Explicit Practically Optimal Alternatives (SPORES)

The chance constraint method (CCM) returns a solution space that meets a desired probability confidence level for a certain objective [12]. The risk averse optimization technique (RVA) is one that is based on calculating the expected utility. It compares 2 random results by finding those results' scalar transformations and determines which one it prefers based on that utility function.

Several artificial intelligent (AI) optimization techniques have been developed. Genetic Algorithm (GA), Particle Swarm (PS) Optimization and Ant Colony Optimization (ACO) are all based on behaviour found in nature. Simulated Annealing (SA) and Artificial Neural Networks (ANN) are also based on AI. GA mimics genetic processes found in organisms like evolution and natural selection to find optimal solutions. PS finds the optimal solution by creating a population of possible solutions and moving them around in the solution space in a swarm like manner. ACO looks to find the optimal path through graphs, based on the how ants do. SA chooses, during each solution iteration, a random step and accepts it in case the solution value is better than during the previous iteration. ANN copies neuron behaviour by addressing data internally and externally.

A different way to analyse optimization problems is by solving it for multiple objectives instead of one. This is done in Multi Objective Optimization (MOO) where, for example, the objective function is solving for both costs and emissions [60]. Dynamic Programming (DP) optimises by assuming that the optimal solution for a problem is directly related to the sub solutions of smaller segments of that total problem. The Multi Agent Approach (MAA) combines multiple algorithms within a single framework to solve more efficiently than frameworks, based on a single algorithm [61].

2.2 Addressing Parametric Uncertainty

In this section, the most relevant method (MCS) that addresses parametric uncertainty will be explained. Subsequently, the reasons why this method is chosen over others are elaborated. As mentioned in the previous section, further explanation about the methods that also have high potential in addressing parametric uncertainty but are not used for this thesis can be found in appendix B.

2.2.1 Parametric Uncertainty: MCA/MCS

Monte Carlo Analysis/Simulation (MCA/MCS) is a structured way to address (exogenous) parametric uncertainty. It operates by taking several samples from probability distributions of uncertain model parameters (inputs, relations) and feeding it to the model, thereby creating many of different scenarios for which the model must find a solution. Since these scenarios are randomly sampled from the distributions of the uncertain variables, both convenient and unfavourable scenarios will be created. The resulting model outcomes can be translated into useful insights by using statistical techniques. A sufficiently high number of samples must be analysed (figure 2.3) to provide reliable results. This number does not mainly depend on the number of stochastic variables but relies heavily on the confidence of the representation of said variables. The ability to accurately represent the stochastic variables in a mathematical way is essential for this technique to work reliably.

One of the drawbacks of MCS is that the number of required samples to produce a reliable result sometimes exceeds reasonable computational demand/time [62]. Possible sub methods that can reduce the amount of runs while maintaining sufficient statistically significant results are latin hyper cube sampling (LHS) [63] and importance sampling (IS) [64]. Furthermore, MCS assumes that the future uncertainties can be defined correctly on this day (meaning that you can (almost) perfectly represent the future uncertainty in a known probability distribution). Insights that can result from MCS are the odds of obtaining a goal, a map on which decision variables are more robust/essential for all the tested scenarios, and the interactions between the model and the inputs/outputs [42]. Within the MCS method, several algorithms have been developed that each approach sampling in a different way, many with their benefits and disadvantages [65].

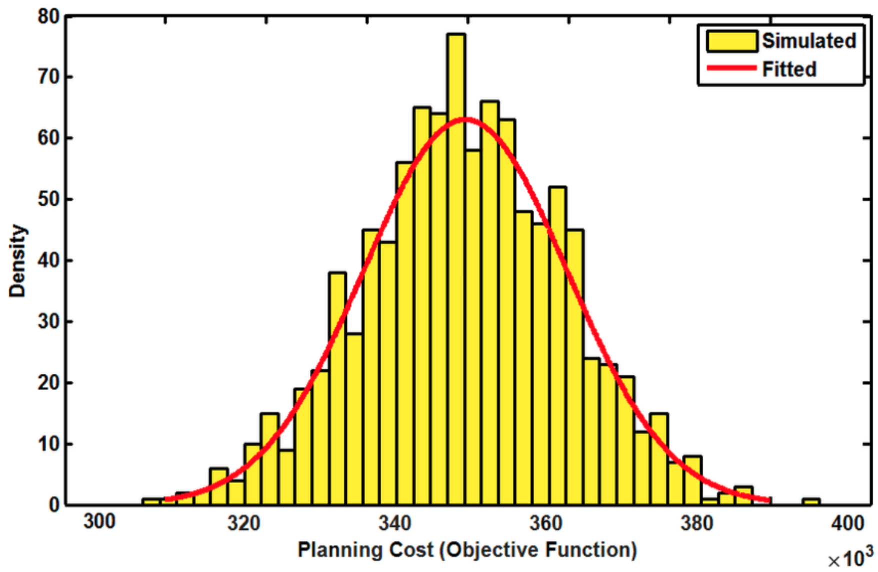

Figure 2.3: Random sampling from a planning cost distribution. Source: Gazijahani et al [3].

MCS can be easily implemented in frameworks in the form of input scenarios. Each sampled dataset from a probability distribution of an uncertain variable results in a scenario that the model can be tested against. It should be noted that for each extra variable that is chosen as uncertain, the number of simulations increases exponentially.

2.2.2 Parametric Uncertainty Method Choice: MCS

Whereas MCS is easy to implement in a recurring method, the other candidates for parametric uncertainty (RO and SP, more information in appendix B) have less applicability. SP works by making decisions before an uncertainty takes place, which is during multiple moments of a given time-series. This is computationally more demanding and harder to program. RO assumes only the expected worst-case scenarios for an energy system, resulting in only one solution that can address all those worst-case uncertainties. However, this is not economically or practically efficient, as this can lead to excessive over-sizing and usually over expensive solutions. In many case studies, the functionality to model for best-case scenarios is also a valuable insight. Providing just an oversized and over expensive result is, in the current day energy system market, not a competitive and contemporary driver. Therefore, using MCS is preferred, as it can address a wider extent of design problems [42] for energy systems.

However, MCS will be represented by a limited number of simple outcomes and probabilities for this thesis. This is chosen as the emphasis of this thesis lies more on the post processing and analysis of the results, and less about the quality of the inputs itself. If we take a large sample size for each uncertain variable, say 50 outcomes, instead of 3 (e.g., base, bad and good outcomes with an equal probability of 33%), then the results will be processed in the same way. However, it will take a lot longer to compute and create said results. Therefore, a simple representation of Monte Carlo scenarios is chosen to represent the uncertain variables for the case studies. How these scenarios will be modelled can be found in chapter 3 (method). Furthermore, MCS can more easily be run in tandem with the available structural uncertainty approaches [42].

2.3 Addressing Structural Uncertainty

Structural uncertainty remains problematic for ESOM. Ordinary approaches to decrease it are exerting expert opinion onto the model design process and implementing more complex relations into the model behaviour to further approach its realistic representation. However, a different and more structured option is discussed further in this section as not all modellers have expert opinion about the relations and properties of the system itself. The near optimal solution space is a useful topic to address this matter [66] and is explained further below.

2.3.1 Structural Uncertainty: MGA

Modelling to generate alternatives (MGA) was initially developed to address public planning problems in the early 80's [67]. It was noted that, next to the optimal solution, additional near optimal solutions can provide very interesting options that can address other problems than what the model solves for. For some energy systems, a 10% increase in cost can be justified and preferred if that extra cost solves for example a societal or political problem.

MGA operates by finding the optimal solution first, and then considers a slack value to add to the optimal result value to create new solutions. MGA assigns an integer weight to each nonzero decision variable from that optimal solution, which is then used in an iterated second optimization, returning a maximally different decision space. The calculation can be adjusted in case more than one near-optimal solution is preferred [52] [42]. The slack value for MGA is chosen subjectively. However, MGA cannot be applied on energy systems with a higher spatial resolution (several locations). MGA only considers the technologies themselves within systems. Therefore, MGA lacks the functionality if insight is required in the spatial distribution of the technologies.

2.3.2 Structural Uncertainty: SPOREs

Where MGA lacks in spatial resolution, Spatially Explicit Practically Optimal Results (SPOREs) makes up for it. This method, developed by Lombardi et al [13], is a spatial resolution extension on the MGA method. Instead of distributing a weight to a certain technology, a weight is attributed to every technology + location combination in SPOREs. If you can have the same technology in multiple locations, several near-optimal solutions provide a different capacity distribution for those locations [13]. Each near-optimal solution is referred to as a SPORE in the remainder of this report. Choosing the number of SPOREs when using the SPORE method is essential in providing a complete result data-set, and is highly dependent on the complexity of the chosen energy system. The slack cost value works similarly as in MGA. The algorithm itself is explained further below.

SPOREs step 1: Find the global optimum of the objective function for the ESM [13] (equation 2.4).

$$\begin{aligned} \text{Minimize } Cost = \sum_j \sum_i (\mathrm{C}_{fix,ij} * \mathrm{x}_{ij}^{cap} + \sum_t \mathrm{C}_{var,ij} * \mathrm{x}_{t,ij}^{prod}) \\ S.t.: A * x \leq b \\ x \geq 0 \end{aligned} \tag{2.4}$$

Where j is the jth location in the spatial domain, and i is the ith technology in the energy system. x_{ij}^{cap} is the installed capacity of one such technology i on location j. $x_{t,ij}^{prod}$ is the power production of one i, j technology location combination. $c_{fix,ij}$ and $c_{var,ij}$ are the discounted financial fixed and variable costs. A and b represent the constraints to which the decision variables x are subject to in the energy system.

SPOREs step 2: A weight w_{ij} is designated to each technology location combination decision variable that has a nonzero result in the global optimum. This weight is assigned by taking the inverse of the (absolute) distance from the average for that decision variable in the previous iterations $(n-1)$ through $\overline{x_i j}$ (equation 2.5 and 2.6). The higher the weight is, the heavier it will be minimised in the next iteration. Meaning that if a technology capacity is close to the average of the previous solutions, it will be more heavily changed in the next iteration. This is the evolving average method [68] [69].

$$\mathrm{w}_{ij} = \left| \frac{\overline{\mathrm{x}_{ij}} - \mathrm{x}_{ij}}{\overline{\mathrm{x}_{ij}}} \right|^{-1} \tag{2.5}$$

$$\overline{\mathrm{x}_{ij}} = \frac{\sum_{ij=1}^{n-1} * \mathrm{x}_{ij}}{n-1} \tag{2.6}$$

SPOREs step 3: A near-optimal solution (SPORE) is now created by minimising the sum of all the weighted technology/location decision variables, while coercing the total objective value to the optimal value plus the added slack (equation 2.7). This is seen as ϵ constrained MOO, in which cost can be regarded as a second objective, although it is not explicitly minimised.

$$\begin{aligned} \text{Minimise } Y = \sum_j \sum_i (\mathrm{w}_{ij} * \mathrm{x}_{ij}^{cap}) \\ S.t.: \mathrm{cost}_n \leq (1 + slack) * \mathrm{cost}_0 \\ A * x \leq b \\ x \geq 0 \end{aligned} \tag{2.7}$$

Where n is the current SPORE number.

SPOREs step 4: This process is then repeated, meaning that (equation 2.5) is applied again to receive new weight values for the decision variables to create yet another near-optimal SPORE.

2.3.3 Structural Uncertainty Method Choice: SPOREs

As each SPORE adds an additional dimension to the solution space, this technique is preferred over MGA. SPOREs can provide a bigger effect on a larger variety of energy systems that have spatial resolution in it, making the final method more universal when SPOREs is combined into it instead of MGA. SPOREs is also implemented in the well-known modelling framework Calliope, where it is continually being improved, making it more state of the art than MGA, which is still based on scoring methods from 1979.

2.4 Method: ESM Frameworks

Several software frameworks have been developed and used to support ESM. Several literature reviews [11] [70] on these frameworks have been conducted, where over 45 different software tools have been analysed on their ability to analyse and calculate energy system insights [10] [27]. An online database with open source energy models is also available [71]. Popular examples are OSeMOSYS, MARKAL/TIMES and the HOMER software, with each their own strengths and unique functionalities.

OSeMOSYS results are generally used for large scale policy expansion. It is based on perfect forecasts and is currently written in the programming languages Mathprog, GAMS and Python. OSeMOSYS uses LP to find optimal solutions and has the possibility to interpret MILP. Electricity and heat are possible energy carriers and OSeMOSYS has been applied to case studies regarding the electricity sector for Africa and South America. Furthermore, OSeMOSYS is obtainable under a free Apache 2.0 License [72] [73].

MARKAL/TIMES also optimises through LP and is written in GAMS. It has been developed by the International Energy Agency (IEA). TIMES is an evolution of the MARKAL software, but both software's are very similar. MARKAL/TIMES are used all over the globe in more than 170 institutions [35] and even has a built-in SP function [42].

HOMER is a software developed by NREL, that has similar functionalities and is already used by some departments of *W+B*. It has a selectable temporal resolution of minutes up to hours and is intended to model systems of a local scale. HOMER does not include the option to model transmission, but does have an implemented sensitivity analysis functionality that can be used to find the sensitive technologies within an energy system. The objective function is economically motivated [70].

2.4.1 Framework Choice: Calliope

The open energy modelling framework CALLIOPE is chosen as modelling environment for the application of the combined structural and parametric uncertainty approach. CALLIOPE is developed by Stefan Pfenninger and Bryn Pickering while they were active in the department of environmental systems science (ETH Zürich) and department of engineering (university of Cambridge). It is freely accessible for commercial and private applications, also through an Apache 2.0 license [74]. It is run through Python and is, as of today, the only framework that includes the SPOREs functionality [75]. It also has the "operate" functionality, which represents a more realistic dispatch strategy based on non-perfect foresight of the future.

2.4.2 Calliope Operation Methodology

Operating under an Apache 2.0 license generally means that there is no big company responsible for customer support. Despite this, Calliope has an active community for debugging, issue solving and software development (updates). Calliope has been developed to be as user-friendly and logical as possible by using internal reliability and solidity within the code. Calliope's design is also intended to be able to handle energy systems with large fractions of variable renewable energy, different spatial (transmission etc.) and temporal (time-steps) resolutions. Additionally, a simplified approach to be able to run models on a high computing cluster has been implemented and to be accessible for many users, the chosen programming language is Python.

Two of the main developers of Calliope and SPOREs are in the employment of the TU Delft, making discussion and code development or tweaking easily possible [75]. Calliope allows both large-scale modelling and small-scale modelling, making it more accessible to be used for many other projects other than the case studies of this thesis. Other frameworks are commonly designed for one scale. Additionally, Calliope does not limit its models to just electricity and/or heat energy carriers, any energy carrier can be defined in Calliope. It is just up to the designer to model the conversion between multiple energy carriers correctly.

Other than the SPORE functionality, Calliope also has the "operate" mode. Operate mode runs a predefined decision variable solution set for a scenario, but with a more realistic foresight horizon. Perfect foresight over the complete time-series is assumed in the default plan mode, whereas in reality planners can only look in the nearby future for a reliable forecast. In operate mode, the model is run with the knowledge that forecasts are only investigated up to 24 or 48 hours in the future [76]. Which can result in long term effects like high temperature in winter being overseen.

Calliope defines a model through yaml files (text files), where all the technical components with their economic and technical aspects (cost/kW, efficiency, ramp up time, lifetime, interest rate etc.) can be defined. These technologies can be generation, conversion, storage, transmission, and demand. Next up, spatial resolution can be defined by creating locations with either coordinates or distances between each other. The designer can define which technologies are available at each location, and which connections between other locations are possible. Lastly, the designer can define the operation settings for the run through the text file. Then, the model can be run by optimising for the best net present value (NPV) of your chosen objective function. An in-depth explanation on how CALLIOPE works, can be found in the online documentation [77].

2.4.3 Calliope Solver Choice

Within CALLIOPE, the optimization solver that is being used, depends on the user. Nonetheless, Calliope has the built-in functionality to switch and use several solvers like the free GLPK, CBC, as well as the commercial GUROBI and CPLEX solvers. Since GUROBI is one of the fastest free solvers available for Calliope (figure 2.4 [4]), and since being affiliated with the TU Delft provides students with a free academic GUROBI license, the choice to use GUROBI for this thesis is made.

Solver	**Solution time**	
	National	**Urban**
GLPK	4:35:40	>5hrs
CBC	0:04:45	0:52:13
Gurobi (1 thread)	0:02:08	0:03:21
CPLEX (1 thread)	0:04:55	0:05:56
Gurobi (4 thread)	0:02:27	0:03:08
CPLEX (4 thread)	0:02:16	0:03:26

Figure 2.4: Solution times for different solvers within Calliope, applied to the national and urban example models. Source: Calliope documentation [4]).

2.5 Uncertainty in ESM

Almost every aspect of an energy system can be modelled as uncertain. But not all variables should be chosen as uncertain since over-complexity reduces the reliability, and increases the computational time of the model. In practice, most model inputs will even be taken as deterministic. This section explains what variables can be taken as uncertain in EMSs, how one can choose which are most important to model as uncertain and elaborate on ways to model them as uncertain.

2.5.1 Choice of Uncertain Variables

The variables that should be taken as uncertain are the inputs that are most likely to change during the operation of the chosen energy system. The variables that fit this description are subject to the energy system that is chosen and are not by definition, always eligible for every single energy system. Some variables fluctuate during the time-span of an energy model, many of which have been modelled as uncertain before [45] [78] [26].

Table 2.2: Overview of commonly modelled variables for uncertain and deterministic operation in ESM.

Variables commonly modeled as uncertain	Variables commonly modeled as deterministic
- Solar yield (Temperature, Cloudiness, Wind speed) - Wind yield (Wind speed, Wind direction) - Demand yield (Heat, Cooling, Electrical) - Hourly electricity price - Fuel prices	- Technical aspects of a component (Efficiency, costs per km, storage self-discharge) - CAPEX of technical components

Although almost any variable is uncertain, some variables are usually modelled in a deterministic way as they do not fluctuate a lot during the time-span of an ESM or since they simply don't supplement to the focus of the energy system when taken as uncertain (see table 2.2).

Although many of these aspects will realistically differ from their expected values, setting them as constant values increases the workability of the model. When making every aspect of the model uncertain, the spread and total uncertainty is also reflected in the results. Over-complexity can then make the calculation insanely long and the results useless, since nothing can be said with absolute certainty. This means that if the uncertainty range is too high, there is no point in modelling at all.

2.5.2 Techniques to Characterise Uncertain Variables

Many approaches are available and have been used to characterise uncertain wind and solar yield [26] [12] [79] [10]. Wind can be modelled by taking Monte Carlo samples from a Weibull distribution, whose parameters can be deducted from historic data [80]. Alternatively, wind can be modelled using the ARMA technique. The ARMA technique uses annual historic wind data-sets to create new yearly data-sets that have similar statistical properties as the provided historic data-sets. Multiple data-sets can be created through this ARMA technique [81] [82]. This could also be applied for demand time-series, but demand has more specific peak correlations around holidays. The TPLF method is a promising method to represent the uncertain aspects of solar data, also based on historic data-sets [83].

Since this thesis is not in essence about the quality of the inputs, it is chosen to model the uncertain variables in a relatively simple manner by basing them on historic data sets (see chapter 3). The goal of this thesis is to show what the method can do with inputs, provided they are correct. Several historic data sources are mentioned in the next section.

2.5.3 Historic Data Sources (Databases)

Reliable data sources should be considered to create data-sets for uncertain variables like solar power, wind power, cooling, heating and electricity demand. Some possible options are mentioned below:

1. The PVgis database, hourly data for potential photo voltaic (PV) panel data [84].
2. The NEDU organisation provides annual synthetic data-sets for energy usage in the Netherlands for gas/heat and electricity [85].
3. Smart meter data from Liander (Network operator in the Netherlands) [86].
4. The Royal Netherlands Meteorological Institute (KNMI), for Dutch weather data [87].
5. Renwables.ninja, an online tool that integrated weather data from NASA MERRA and CM-SAF' SARAH to provide pv and wind data-sets for every location on the world [5].

For this thesis, renewables.ninja [5] is used to extract solar PV data and temperature, which can be used to create the time-series for PV production, cooling and heating demand. NEDU's synthetic data-sets [85] are used to create the electrical, heating, and cooling demand for the cases. Many more sources are available, but for the application of the case studies the above mentioned sources are sufficient to find reliable historic data for case studies in the Netherlands.

2.6 Thesis Scope

2.6.1 General Scope

This thesis is not focused on the optimization of existing energy systems, but on future systems that still have to be designed. It aims to combine parametric and structural uncertainty, by combining the MCS and SPOREs approach respectively (see section 2.2 and section 2.3) within the Calliope framework (section 2.4), which has not yet been done before and is recommended as future research for the SPOREs approach (the inclusion of parametric uncertainty within SPOREs) [13]. The solver used in Calliope is GUROBI since it is the fastest and free under an academic license (section 2.4). The method is applied to two case studies, a simple case 1 (test case) and case 2, to test and validate its effectiveness. The scale application in this thesis is at uttermost on district level for both case studies, despite its proven effectiveness for national scale energy systems [13]. Applying SPOREs at district level is also be novel, as it has been used before only on national levels.

2.6.2 Stochastic Variables

Bearing in mind feasibility and limited computational complexity, only 2 and 3 variables are considered as uncertain for case 1 and case 2 respectively. These variables are represented by modifying historical data. For demand, it is within the scope to model actors that deviate from the average usage profile, but (as decided in a progress meeting) modelling per minute instead of per hour is not within the scope of this research since it increases the computational requirements exponentially and does not change the processing steps. This does mean however that some of the optimised capacities might not be high enough to cope with realistic peak moments. This problem can easily be tackled by including additional constraints.

2.6.3 System Modelling

It is within the scope of this thesis to model the physical models in a way that the components are represented reasonably.

1. *Timeseries:* The model's temporal space is hourly, and the runs last for a year.
2. *Integer or continuous programming:* Discrete decision variables are not be used in this model as continuous variables decrease solution time.
3. *Cyclic storage:* The state of charge (SOC) of the storage components at the start of the model runs are set equal to the final SOC of the model run.
4. *Efficiency:* Degradation or fluctuation of efficiency is not considered, and efficiency is constant and equal to the average one from product specification or current day values.
5. *Ramp up time:* Ramping of components is only modelled if they are known and significantly relevant compared to the hourly based time-series that are used.
6. *Curtailment:* PV panel production is not curtailed.
7. *CO_2 emissions:* Any component with known operational CO_2 emissions, is programmed to include its carbon footprint in the model in a realistic manner. The CO_2 emissions emitted during component production are included in the model as well if a reliable source is available.

2.6.4 Outside Scope

This thesis does not include in-depth research on how to model the uncertain variables correctly. The validity of those stochastic variable representations is gazed upon briefly (in section 2.5) to provide sufficient data quality. The value of this thesis lies within the method, and not in the representation of the uncertain variables. Predicting the future is therefore not central in this thesis but having a proper way to interpret that/any future, no matter what shape it takes, is. Global Sensitivity Analysis is also out of scope.

3 Method

Each step of the method is explained and visualised in depth in order to help understand its workflow in this chapter. Subsequently, both case studies to which this method will be applied, are explained in section 3.2 and 3.3. Case 1 is mainly used as an exploratory case to see if the method is applicable and works for these types of energy systems. Therefore, due to the similarity between the case 1 and case 2 results, case 1 is only explained briefly in this and the next chapter. An in-depth explanation of case 1 and its results can be found in appendix A.

3.1 Computational Workflow

In essence, the computational workflow has 7 parts (figure 3.1). It starts with the *Inputs*, where the components of the energy system model are defined and where the uncertain variables are chosen. Subsequently, the first optimization calculates all the possible solution ranges that the components can have, also called the *configurations solution space*, by choosing the amount of SPOREs and an allowed cost slack value in the *Optimization Strategy*. In this solution space, only component ranges that work very well for the energy system under the chosen uncertain variables are created. However, this *Configurations Solution Space* is still a very large set of component ranges that must be filtered into configurations that are most promising and interesting for the chosen energy model. This filter is applied in the *Configuration Selection*. The result of this filter is a small set of *Testable Configurations*. In the *Evaluation*, each of those configurations is tested versus all the input scenarios on a set of chosen performance indicators, like cost and security of supply. The results of that second optimization are found in the *Results*. These results are in the form of performance scores, statistical figures, and statistical statements. For the remainder of this chapter, each method step is explained in detail, followed by an encapsulated overview.

3.1.1 Inputs

Firstly, the inputs and the energy system model itself are defined. The relevant uncertain variables are chosen, and their data-sets collected. The parametric uncertainty is addressed by choosing several outcomes that the chosen uncertain variable can take on, and by giving each of those outcomes a probability of occurrence as is also done in MCS. In figure 3.2 and figure 3.3, an annual time-series of two possible uncertain variables “solar yield” and “temperature” are visualised. Multiple data-sets should be used with each a certain probability of occurrence for each uncertain variable.

All the possible technologies and, if applicable, all the spatial locations of the chosen energy system must be defined in Calliope through the yaml files [77]. A simple duplex house energy system is used to explain all the steps of this method. The spatial configuration of this simple duplex house energy system is displayed in figure 3.4. In this example energy system there are 3 locations, interconnected by electricity cables and with solar panels, batteries, grid connection and electrical demand as possible technologies. Any physical or other capacity constraints like the maximum square meters available for solar panels, are defined in the yaml files as well.

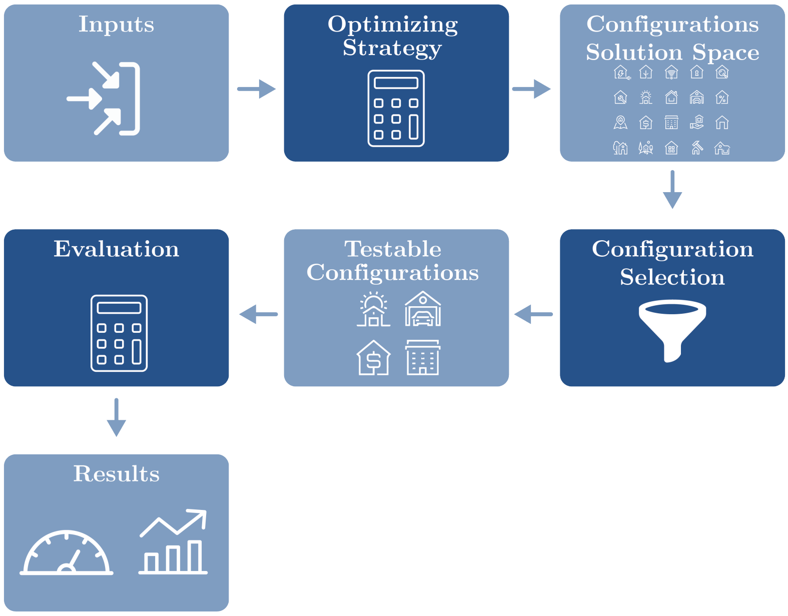

Figure 3.1: A simplified version of the methods' workflow.

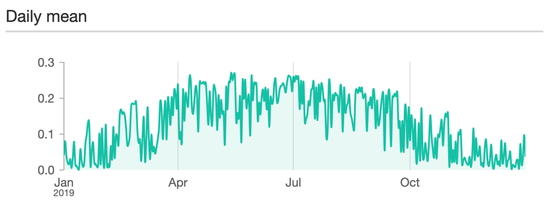

Figure 3.2: Annual solar yield as an uncertain variable. The graph shows the average Solar yield in [kW/hour/m2] of installed PV panels, in The Netherlands in 2019 [5]. This time-series represents south faced panels, under an inclination of 35°.

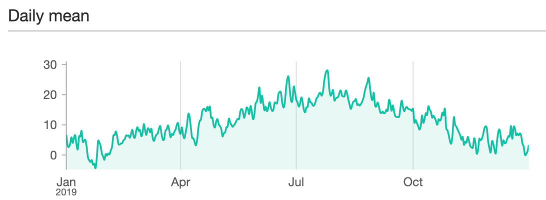

Figure 3.3: Annual temperature as an uncertain variable. The graph shows the average temperature [C°] per hour, in The Netherlands in 2019 [5]. This time-series represents temperature at a height of 2 m.

For this thesis, all the data-sets for uncertain variables that are related to historic weather conditions are based on measured weather conditions in a central point in the Netherlands (De Bilt), taken from the data sources mentioned in section 2.5. Other uncertain variables are based on averages in the Netherlands. This means that the random selection that usually happens in MCS, is not detained. However, the resulting data-sets still represent a realistic and similar data-set compared to a randomly sampled MCS, and it improves the calculation time immensely. The data-set format that Calliope uses is the "ISO 15927-4:2005" standard. This is a standard that reads data for time-series in the form of 'yyyy-mm-dd hh:mm:ss' [88].

3.1.2 Optimization Strategy

With the energy system model and uncertain variables defined, the simulation options can be chosen. Options like the number of SPOREs (number of near optimal solutions), its slack value [%], and for what time-span the scenarios are run (time range and the time-step size) are defined. Additionally, the solver choice, (multi) objective function and cyclic storage are also prescribed.

For the Optimization Strategy phase, additional simulations are conducted to improve the methods' effectiveness. Two simulation options are varied since it is expected that they are most influential on the effectiveness of the workflow/method:

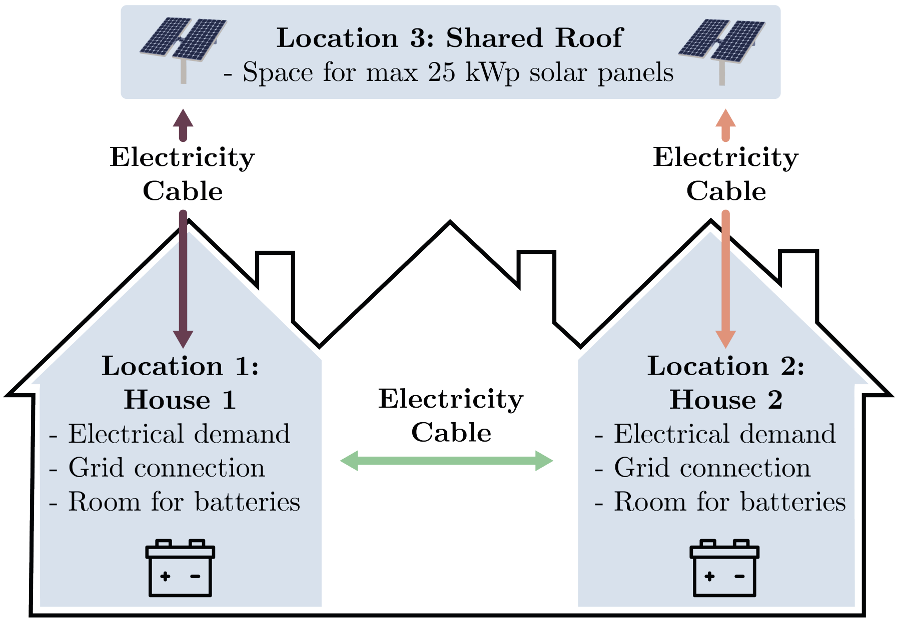

Figure 3.4: The spatial configuration of a simple energy system for a duplex house. All locations have different possible technologies and can be connected by electricity cables with different distances. In locations 1 and 2, electrical demand, the grid connection and batteries are possible technology options. In location 3, there is room for solar panels to be installed [6]

- *Cost slack for SPORE options:* How does using a low slack (15%) or a high slack (50%) value affect the results and the way to process them?
- *The number of SPOREs:* The more complex a system is (more technology/location combinations), the more SPOREs are desired if all possible options are to be considered. However, how does changing the number of SPOREs created between a high number (50) and a low number (15), change the reliability/resolution of the stage 1 results for the main case?

Both additional simulations are tested on case 2 to improve the simulation options decision making process for the method in future cases. The results can be found in chapter 4.4.

3.1.3 Configurations Solution Space

After the optimization strategy simulations, Calliope will return several solutions, equal to the amount of Monte Carlo scenarios (input scenarios) multiplied by the number of SPOREs + 1 (equation 3.1). All of these (near) optimal solutions for all the given input scenarios combined, are called the configurations solution space.

$$\#ofsolutions = \#MCS * (SPOREs + 1) \tag{3.1}$$

One single solution is either the cost optimal (SPORE 0) or a near cost optimal result (SPORE) for the energy system, for one of the input scenarios. This contains the technology capacities per location for all the components (four examples of single solutions can be found in figures 3.5, 3.6, 3.7 and 3.8), as well as the best way to use those capacities through real time behaviour (dispatch) of the system through time-series data (see figure 3.9).

Although a single solution already provides a lot of information about how a solution can behave for a specific input scenario, it does not yet provide a decision-making design strategy for the energy

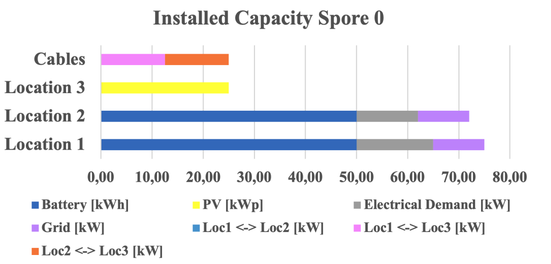

Figure 3.5: Solution 1 (optimal solution, SPORE 0) for one input scenario. The optimal and cheapest solution only uses two electricity cables (loc1-loc3 and loc2-loc3). The max PV amount is installed and both locations have 50 kWh of battery installed.

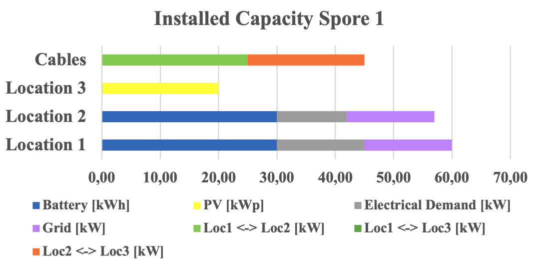

Figure 3.6: Solution 2 (SPORE 1) for one input scenario. With an increased cost equal to the optimal cost plus the slack, the result is different than the optimal one. In SPORE 1, a different electrical cable is used, while less PV and battery is installed.

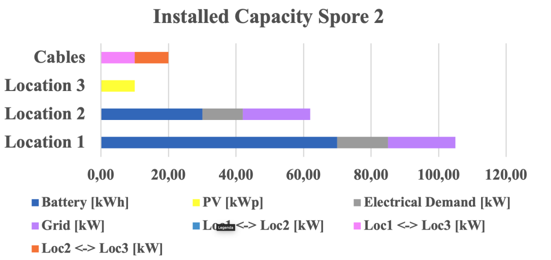

Figure 3.7: Solution 3 (SPORE 2) for one input scenario. With the same cost, the second SPORE results in a configuration with fewer electricity cables, fewer PV panels, and a spread-out battery capacity. This configuration depends more on grid electricity.

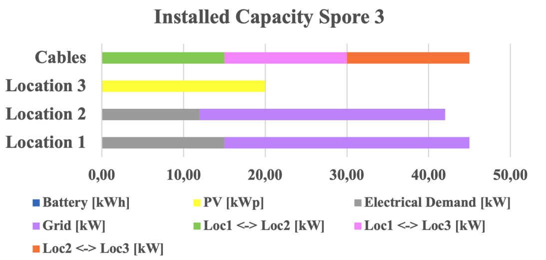

Figure 3.8: Solution 4 (SPORE 3) for one input scenario. With the same increased cost, the third SPORE results in a configuration with a lot of electricity cables, an increased grid connection, an average amount of PV panels, but no batteries.

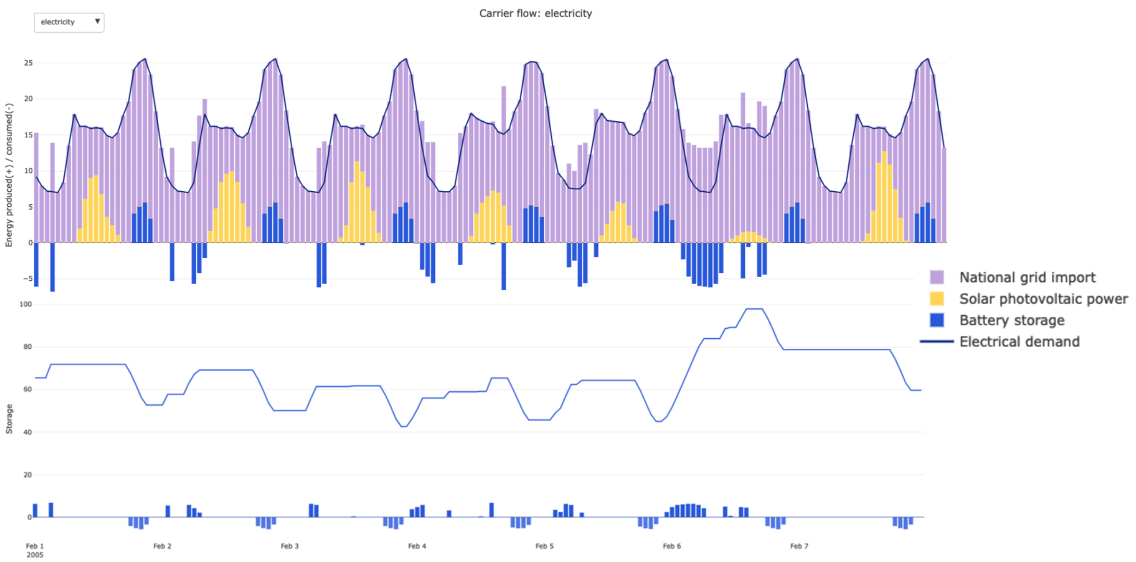

Figure 3.9: The time-series in [kW] for electricity and electrical storage of a single solution.

system that is robust against all the input scenarios. The whole configuration solution space (all the single solutions, for all the input scenarios) must be used in a way to detect what (type of) solution works best for all the possible input scenarios. One convenient way to obtain that, is by visualising the complete configuration solution space in capacity box-plots (see figure 3.10).

Several statements can already be made about the energy system, when comparing the full configuration solution space in box-plots:

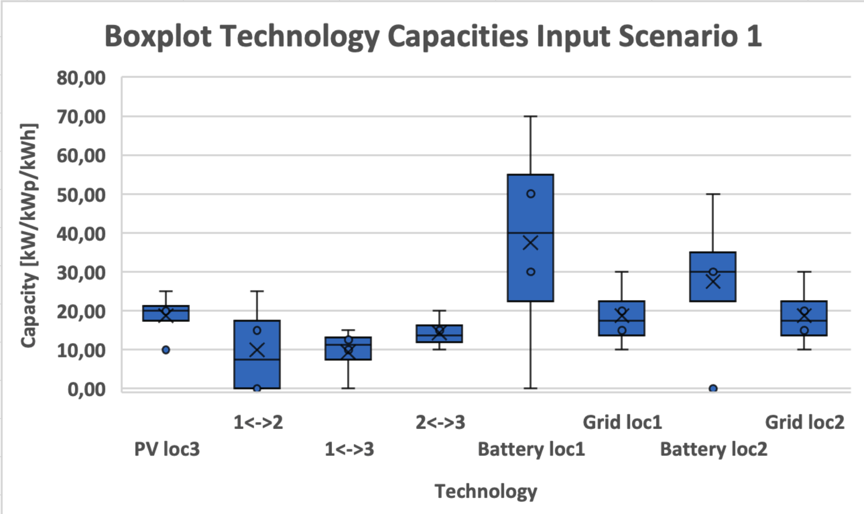

Figure 3.10: The technology capacity solutions for SPORE 0, 1, 2 and 3, for one input scenario, visualised in a box-plot. Battery loc1 has a larger spread than the electricity lines between 2 and 3.

- Certain **relations** within the **model** can then be defined:
  - The installed electrical demand capacity is directly connected to the input scenario. If an input scenario has high electrical demand, then the installed electrical demand will be equal to the max electrical demand.
  - The total cable capacity that is connected to location 3 (PV location) must be able to cope with the maximum PV yield.
- Certain **technologies** can then be identified as **(non-) Essential**:
  - The electricity cable between location 2 and 3 is never equal to 0, making it essential for all the input scenarios.
  - Both location 1 and 2 always need a grid connection.
- Identify the **certainty range** of technologies, a larger data spread means a more sensitive technology (-location combination):
  - The installed battery capacity has a very large spread, meaning that the battery technology is sensitive to the inputs.

Despite providing useful knowledge, it does not tell designers yet which configurations are most interesting to test against all the input scenarios. Therefore, a reliable and systematic configuration selection method is desired.

3.1.4 Configuration Selection

To obtain the best design configurations, two approaches are applied in this thesis. The first approach chooses design configurations by simply selecting specific single solutions from the configurations solutions space based on extreme values like the maximum or minimum installed capacity of a particular technology(-location) combination. This way, a configuration can be selected because it had the highest battery capacity from the complete configurations solutions space, or because it was simply the cheapest option. This approach is very subjective and ignores many repetitive technology correlations among all solutions and will likely result in unnecessarily low performance scores in the final results as many of these solutions are created through SPOREs (which promotes diverse solutions). Therefore, a second "advanced configuration selection" is also designed to use a more structured procedure. The subjective "cumbersome" selection procedure is used for case 1. While the advanced configuration selection approach is tested and applied in case 2.

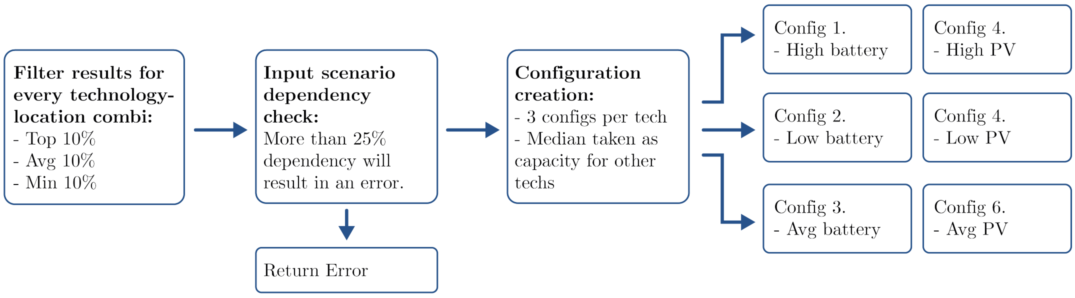

Figure 3.11: Workflow of the advanced configuration selection.

The improved configuration selection method tries to automatically utilise repetitive correlations between technologies by filtering a set of solutions and using those correlations to create configurations to test to obtain the final results. If a "top 10% capacity for technology A" filter is applied, and if all those filtered solutions also show a high capacity in technology B, then a repetitive correlation is found and utilised (see figure 4.22). The "improved configuration selection" algorithm is implemented (figure 3.11) to automise this process for all correlations and technologies. For each technology/location capacity combination, a "top 10%", "bottom 10%", or "average 10%" capacity filter is applied to the complete configuration solution space. Subsequently, an additional dependency check is conducted to make sure that these correlations are not too dependent on particular input scenarios instead of the technologies themselves. This check inspects from which input scenario each result from the currently used 10% filter is, and checks if they have a large enough diversity. This is done by counting the amount of times each input scenario is used for the filtered results, and dividing (normalizing) that count by the total number of solutions in the 10% filter. If more than 25% of the filtered results is dependent on a single input scenario, any correlation found can not be devoted to the energy system and the technologies, making it unhelpful to analyse that configuration further. If the dependency check shows that the filtered results are less than 25% dependent on a single input scenario, then the results of that current filter are used to create a testable configuration. This testable configuration is created by taking the median of the filtered values of each technology/location combination.

3.1.5 Testable Configurations

1 testable configuration is created per applied filter for each technology/location combination thanks to the advanced configuration selection method. These testable configurations are all based on the correlations of all SPOREs and optimal solutions (the complete configuration solution space). Depending on how complex the energy system is, the number of testable configurations can be high. The resulting testable configurations are now be tested against all the possible input scenarios for certain performance scores.

3.1.6 Evaluation

Calliope is once again used to test the performance of each selected configuration against all the possible input scenarios. Calliope has two ways to test an energy system with predefined capacities for different input scenarios: plan mode and operate mode. Plan mode is used for this thesis. Subsequently, Calliope uses the configurations from the testable configurations step as additional input for each scenario. This means that each configuration is run for every input scenario. The resulting outcomes are then used to score each configuration on certain performance indicators, used for the final results.

Many criteria can be used to determine which configuration is the best one. Indicators can be cost [EU NPV], security of supply (SOS) [%], CO_2 emitted [kg NPV], grid dependency [%], capacity factors [%], LCOE [EU NPV], unmet demand [kWh], self-dependency [%], redundancy [-], and many more. Just 3 scoring indicators are used for case 1, whereas just 4 of these are chosen as scoring indicators for case 2. CO2 emissions, cost, SOS and grid dependency are chosen for case 2. Each result is scored on these performance indicators and visualised by histograms, tables, time-series and other plots (see next section) after Calliope's plan optimization.

All the unmet demand (heating, cooling and electrical) of the total time-series is calculated and divided by the total demand (equation 3.2) to calculate the security of supply (SOS). For the total cost, the net present values (NPV) for all technology and operation costs are calculated and summed (equation 3.3). For the total CO_2 emissions, a similar calculation is applied to the time-series (equation 3.4). To obtain the grid dependency, the total electricity, extracted from the grid, is divided by the total amount of energy consumed by all the demand (equation 3.5)

$$\text{Security of Supply (SOS)}[\%] = \frac{(1 - \text{Unmet demand [kWh]]})}{\text{Total demand [kWh]}} \tag{3.2}$$

$$\text{Total Cost [Euro, NPV]} = \sum_{i=1}^{tech:loc} \text{CAPEX}_i + \text{OPEX}_i(t) \tag{3.3}$$

$$\text{Total CO}_2 \text{ [kg, NPV]} = \sum_{i=1}^{tech:loc} \text{CAPEX}_i + \text{OPEX}_i(t) \tag{3.4}$$

$$\text{Grid Dependency [\%]} = \frac{\text{Electricity from grid [kWh]}}{\text{Total consumed demand [kWh]}} \tag{3.5}$$

with i = each technology/location combination

3.1.7 Results

For each selected configuration and input scenario combination, the entire time-series of optimal dispatch is conducted (figure 3.12) by Calliope. The scoring parameters are generated as explained in equations 3.2, 3.3, 3.4 and 3.5 from these results.

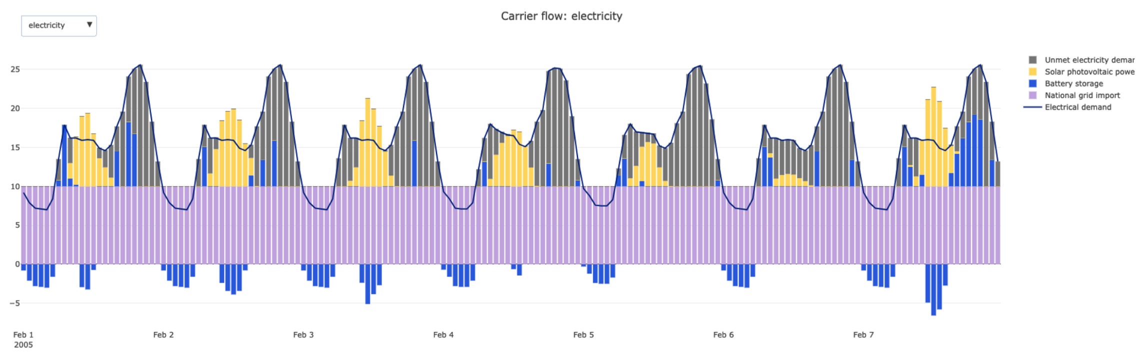

Figure 3.12: A result time-series for electricity [kW], for a selected configuration and one of the input scenarios. Despite always using the maximum grid capacity, in February, there is still unmet demand thanks to the lower solar yield. This unmet demand is used to calculate the Security of Supply.

These performance indicators are calculated for each configuration for each scenario. Subsequently, a histogram is generated by multiplying each score with its probability of occurrence (figure 3.13) to visualise all these performance scores simultaneously for one configuration versus all input scenarios. A ridge plot is used, to visualise all possible configurations for one performance indicator, against all the input scenarios. All these histograms are visualised simultaneously in a ridge plot (figure 3.14).

The obtained data is used to calculate statistical data like the mean values and standard deviations. An overview of all the performance indicator scores, for all the configurations, against all the input scenarios, is also made clear in a table. The mean of a set of data-points is obtained by (equation 3.6).

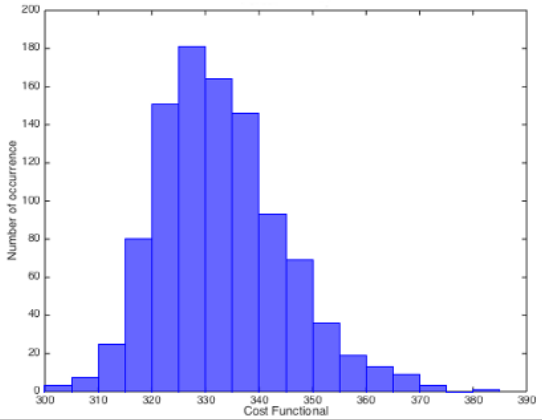

Figure 3.13: An example of a total cost. In the histogram plot, all results in between two bin limits will be summed to obtain the total count for that bin. The total amount of input scenarios is equal to the total count. Source: Delle Monache et al [7].

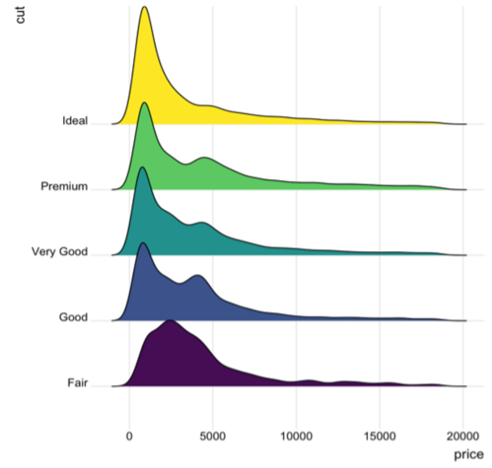

Figure 3.14: An example of a ridge plot. For each testable configuration (in this plot represented by “ideal”, “premium”, “very good”, “good” and “fair”), the histogram for one performance indicator can be plotted in a ridge plot. Source: Holtz et al [8].

The standard deviation is found by taking the square root of the variance, defined as in (equation 3.7) [89].

$$\text{Mean } \overline{x} = \frac{\sum_{i=1}^{n} \mathrm{x}_i}{n} \tag{3.6}$$

$$\text{Standard Deviation } std = \sqrt{\frac{\sum_{i=1}^{n} (\mathrm{x}_i - \overline{x})^2}{n-1}} \tag{3.7}$$

Where n is the total number of data-points, and i is the ith data-point. If the input data represents the parametric uncertainty in a realistic manner, these results are used for the design strategy of the energy system. When considering the possible configurations from the advanced configuration selection, one can now state which configuration has the highest robustness regarding SOS, grid dependency, CO_2 emissions or cost. With these results, one can state that the probability for a chosen configuration to meet a certain budget is equal to XX% within the given input scenarios.

The results can also be visualised by plotting two performance indicators against each other. Amongst energy system designers, it is often interesting to find the cost of unmet demand. This is obtained by showing both the total cost results and the security of supply in a single plot (figure 3.15).

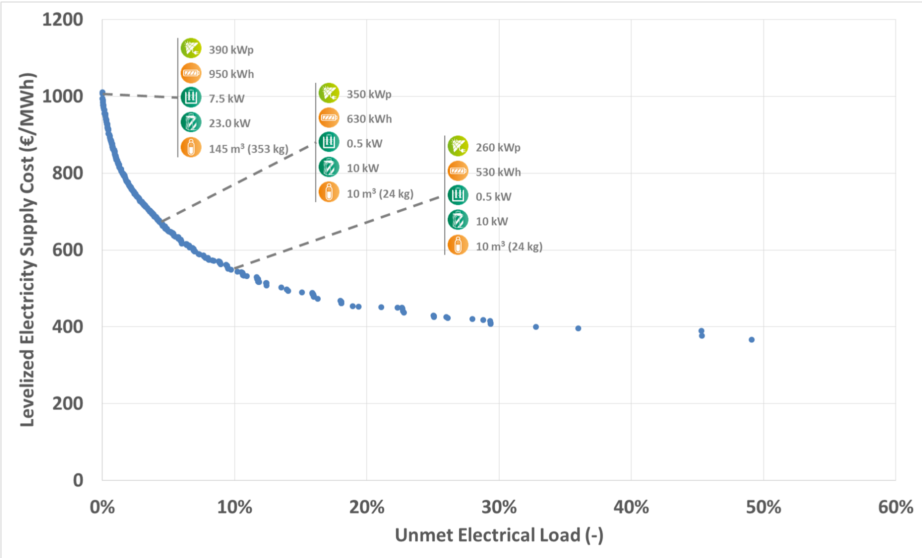

Figure 3.15: The performance of all chosen configurations against security of supply and cost. Each blue dot represents a testable configuration. Source: Seed Energy [9].

3.1.8 Recap Workflow

The complete workflow is now filled with useful settings (figure 3.16).

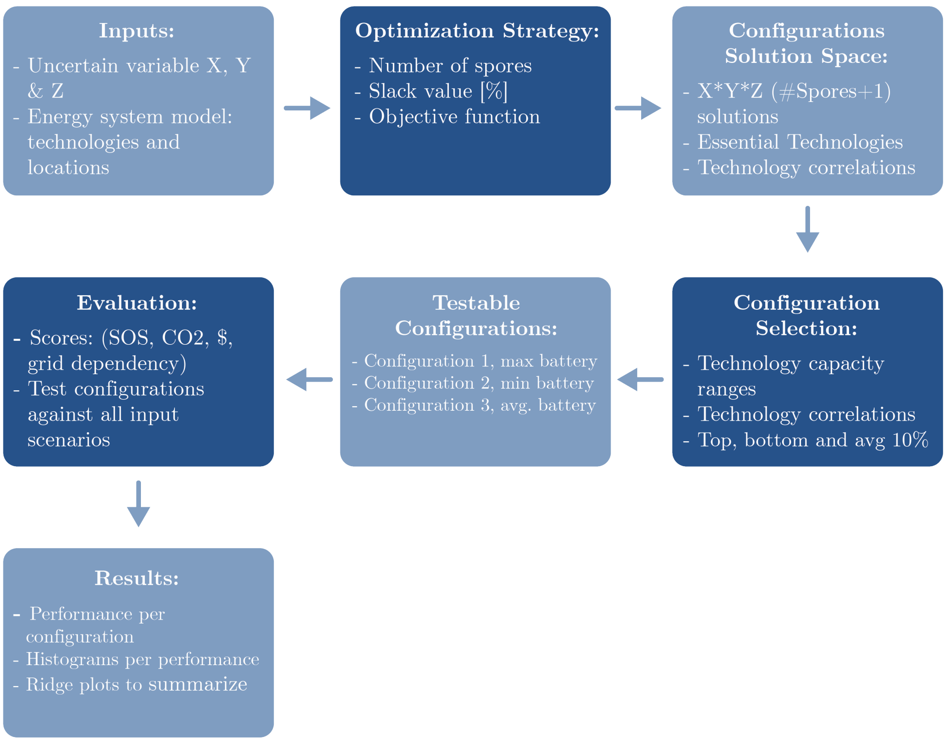

Figure 3.16: The filled workflow.

3.2 Case 1

As mentioned in the introduction of this chapter, case 1 (test case) is a relatively simple energy system. It is designed to discover Calliope's capability to execute of the workflow described in section 3.1. However, since case 1 does not provide extensive meaningful additional results, compared to the case 2 results, its background and results are discussed only briefly here and in chapter 4. Case 1 is designed to address the following features of ESM:

- Transmission losses
- Battery losses (round-trip and self-discharge)
- The impact of high and low demand on different locations
- Choosing between two PV types with different efficiencies, when installed in two possible inclinations.
- The impact of different demand profiles
- The impact of different solar profiles.

The energy system consists of two clusters of 3 households (figure 3.17). The first cluster of 3 households on location X1 has a combined roof surface of 60 m^2, with an inclination of 50°pointed towards the south. The other cluster of 3 households on location X2, has a combined roof surface of 100 m^2, but its inclination is 0°(flat roof). The only grid connection of the system is located on location X3. The electricity can flow to, and from these 3 locations through electricity cables that have certain losses per kilometre. On each household cluster, two types of PV panels (type 1: low efficiency & cheap, type 2: high efficiency & expensive) and batteries can be installed. Regarding electricity demand, the households on location X2 are modelled as above average electricity users (1.1* national average), while the houses on location X1 are modelled as average electricity users (national average).

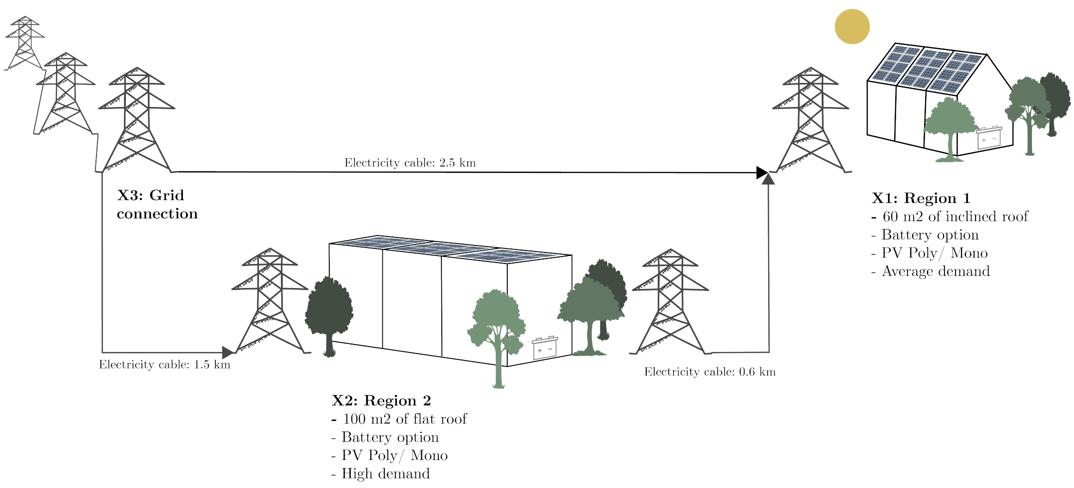

Figure 3.17: The spatial configuration of case 1. 3 locations are connected through electricity cables.

The two chosen uncertain variables for case 1 are solar yield and electrical demand. Uncertain solar yield is realised by taking 15 years of historical solar data (2005-2019) from [renewables.ninja] for a location in the Netherlands. For the electrical demand, the average annual electrical consumption is multiplied by fractional hourly electrical consumption profiles. More information can be found in appendix A. The most important chosen simulation settings are a 15% cost slack, 5 SPOREs and the cumbersome configuration selection method.

3.3 Case 2

Case 2 is based on a project [90], that is similar to a currently ongoing project within W+B. Many assumptions are made, based on current day values and reasonable estimates. These assumptions and their sources can be found in appendix C.

3.3.1 Energy System Configuration

The energy system for case 2 consists of 100 households with electrical, heating, and cooling demand profiles. To meet these demand profiles, multiple energy carriers are introduced to the energy system, namely electricity, heating water, cooling water, and hydrogen.

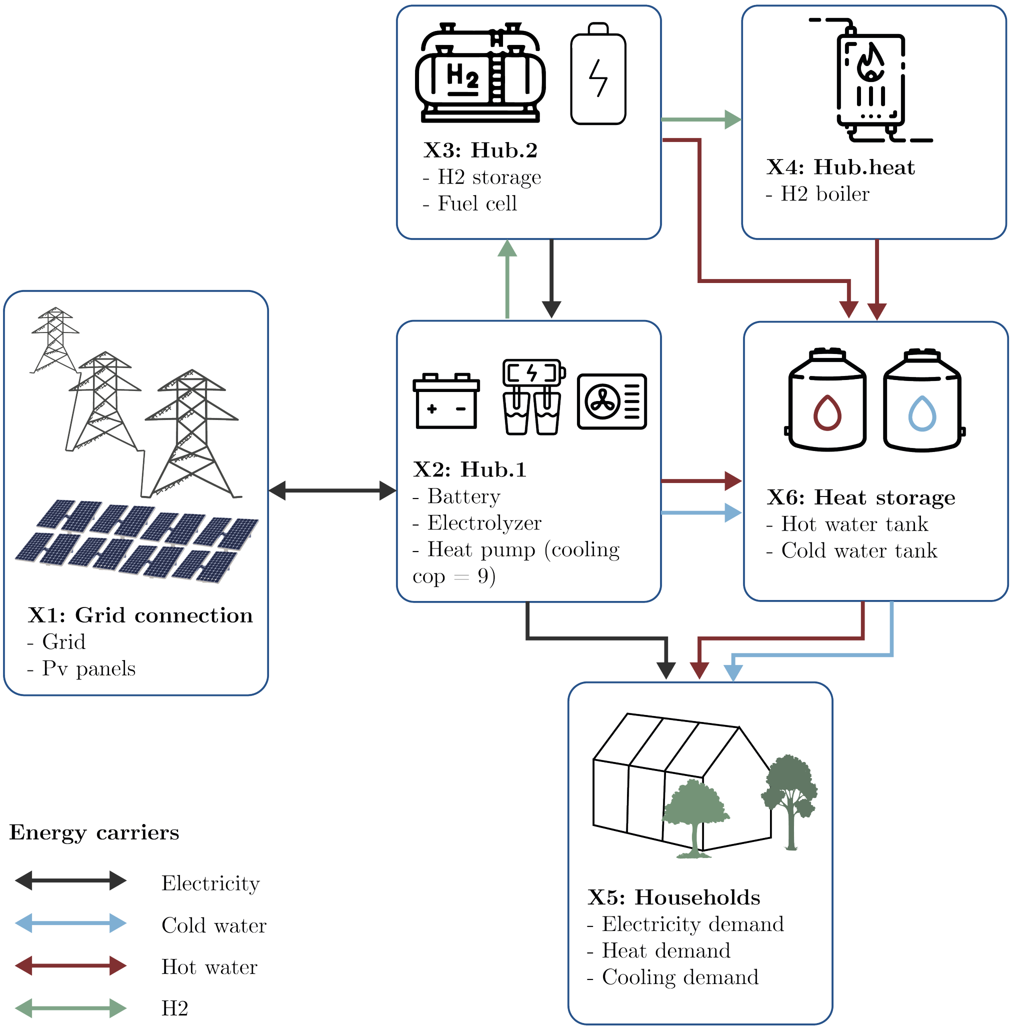

Figure 3.18: Energy system spatial configuration case 2.

As visualised in figure 3.18, there is a grid connection available for this energy hub (system) and there is a connection available for all the installed solar panels. The electricity can flow between the grid connection, solar panels, battery, electrolyzer, fuel cell and electrical demand. The electrical demand, heat pump and electrolyzer can only consume electricity, while the fuel cell and solar panels can only create electricity. The grid and battery can both consume and create electricity. Hydrogen is created by the electrolyzer and flows towards the hydrogen storage, where it can either be stored or sent to either the hydrogen boiler (for heat production) or to the fuel cell (for electricity production). In order to meet the cooling demand, only the heat pump can be used by converting electricity to cooling water with a coefficient of performance (COP) of 9. The heating water can be extracted from the electrolyzer waste heat, fuel cell waste heat and the hydrogen boiler. There is hot and cold water storage available for both the heating and cooling demand. The electrical, heating and cooling demand represent the needs of a 100 households. Most connections are unidirectional and some are bidirectional, depicted by the arrow type used in the figure. Assumptions and explanations about all technical aspects of these components, can be found in appendix C.

It must be noted that the heating system is simplified in this version of the energy system since all energy carriers are connected to each other directly through its energy value [kWh]. For heating and cooling, a fixed temperature difference is used to connect the conversion rates. A more realistic but complex version of this energy system is therefore recommended in the future research. In this complex version, the heating and cooling quality should be considered as well.

Since each individual non-transmission technology is only allowed at a single location, the technology/location combinations have no additional functionality for this energy system. Furthermore, since the case 2 energy system is small scaled, the cost contribution for the transmission technologies is very low compared to the other technologies. Meaning that a change in transmission capacity between locations, while having a large effect, is not expensive. A variable transmission technology would often not be considered on this small scale in practice, but depicted by standard oversized regulations. For that reason, the energy system for case 2 is modelled without transmission technologies to increase the focus on the technology distributions. This choice greatly reduces the computational time and complexity, while barely affecting the objective function (cost) and its results.

3.3.2 Modelling Assumptions and Choices

For the main thesis case study (case 2), 3 variables are taken as uncertain: "Solar Yield", "Energy Demand" (electrical, heating and cooling) and "grid electricity price". The choice is made to use an "average" year, take historic data from that year, and then create an average (base), a good (+10-20%), and a bad (-10-20%) outcome with equal probability of occurrence (33%) for each uncertain variable. With 3 possible outcomes for each of the 3 uncertain variables, 27 input scenarios are defined (3*3*3). This approach is chosen to simplify and therewith reduce the computational time of the results, as the added complexity does not change the post processing approach but does only increase the calculation time significantly. As mentioned earlier, this does not exactly represent the random sampling process that normally happens in MCS, but it does create a data-set with similar properties as MCS would produce.

As this energy system is a complex one with many components, many assumptions are made by consulting multiple sources. Values are based upon current day market values, invoices, technical data-sheets, and common sense. The used specifications and an in-depth elaboration on all the parameters can be found in appendix C.

3 variables are modelled as uncertain, with each 3 equally probable outcomes (table 3.1):

1. Grid electricity cost (base 33%, high 33%, low 33%)
2. PV yield (base 33%, cloudy 33%, sunny 33%)
3. Demand (base 33%, extreme 33%, frugal 33%)
   (a) Electricity (S21).
   (b) Heating (DHW+TH).
   (c) Cooling (TH)

To compute the grid electricity price, historic time-series of Dutch grid data for 2017 are used and multiplied with 1.2 and 0.8 respectively to create a high and low scenario. Afterwards, a carbon tax of 150 [EU/kg CO_2] (0,03 [EU/kWh] for the expected energy mix in 2030) is internalised by adding it to the grid price time-series. For the PV yield, measured data for the year 2017 for location "De Bilt" is used and multiplied with 0.9 and 1.1 respectively. For demand, 3 equally probable possible

Table 3.1: Input scenarios for case 2.

Grid cost scenario	Pv scenario	Demand scenario	Total scenarios
Base	**Base**	**Base**	
High (+20%)	**Cloudy (-10%)**	**Extreme (+20%)**	
Low (-20%)	**Sunny (+10%)**	**Frugal (-20%)**	**3*3*3 = 27**

outcomes are chosen for 100 A-labelled households in 2017. Average values for electrical, heating, and cooling demand are used as input time-series for the base outcome. High values are used for all three demand types simultaneously in the extreme case. For the frugal case, only low demand values are used as input. All time-series are modelled as hourly time-series for 1 year (8760 data-points). Certain physical and political assumptions about the minimum and maximum capacities for PV, hot storage, cold storage, hydrogen storage, electrolyzer and fuel cell technology are made, and can also be found more elaborately in appendix C.

Notable constraints assumed/chosen for Case 2:

- PV: Minimum is 375 kWp (kilo Watt peak), maximum is 750 kWp (available rooftop area). Minimum is 50% as newly built houses are highly likely to have PV panels on them.
- Cold and Hot water storage: Physical Maximum of 125 m^3 for 100 households for both types of storage. (2187.5 kWh hot storage, 730 kWh cold storage with dT's).
- Hydrogen storage: Minimum 1 tube trailer, maximum 5 tube trailers (safety).
- Electrolyzer = minimally 20% of average total demand per hour (avg demand = cooling + heating + dhw (domestic hot water) + electricity = 210 kWh/hour) –> 0,2 * 210 = 42 kW.
- Fuel cell = same as minimum electrolyzer –> 42 kW minimum capacity.
- Minimum grid capacity of 3450 kW.

3.3.3 Simulation Options

- Time-series (1 year, hourly)
- 3*3*3 = 27 "Monte Carlo" Scenarios
- SPOREs: 50 per scenario (15% slack), Evolving Average Method.
- Objective function = Minimise cost.
  - Grid CO_2 is internalised through 150 EU/Ton CO_2 tax.
  - 27 MCS * 50 SPOREs = 1350 solution configurations.

3.3.4 Visualised Input Data

The uncertain variables are modelled and shown as annual time-series in figures 3.21, 3.20, and 3.21.

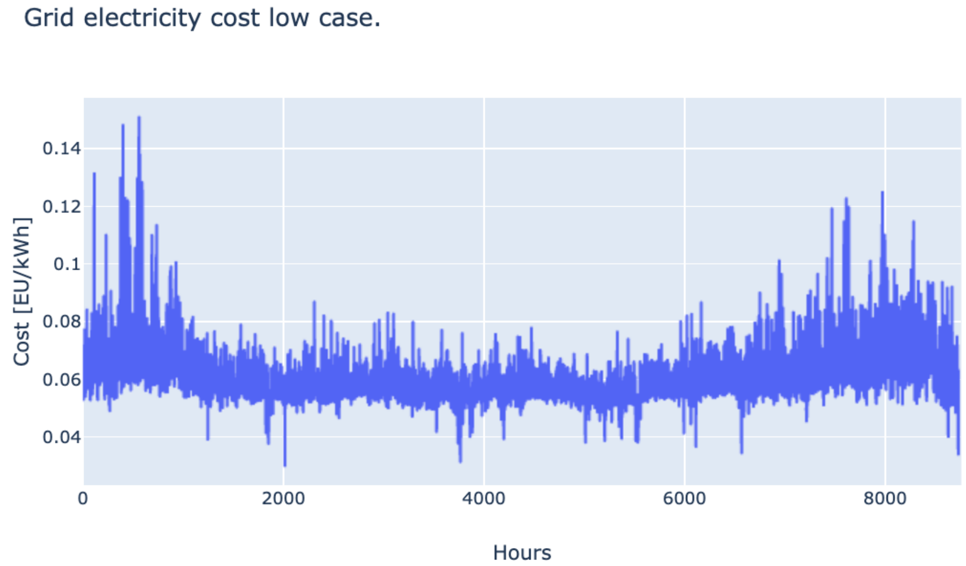

Figure 3.19: An example of an annual time-series for the grid electricity price in the Netherlands in 2017.

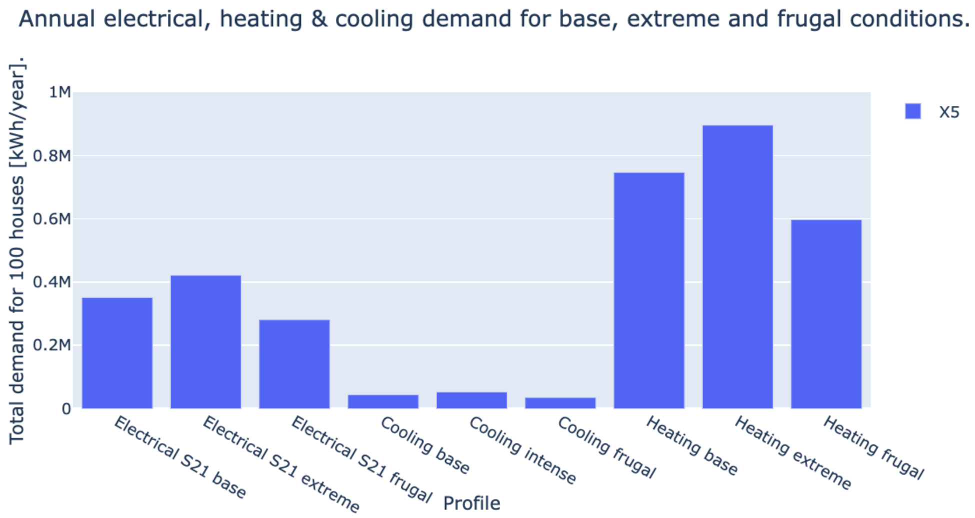

Figure 3.20: The annual demand for electricity, cooling and heating for case 2 (Appendix C).

3.3.5 Recap Additional Simulations

The workflow of the method as described in section 3.1 is applied in the context of case 2. However, additional simulations are conducted to case 2, while changing certain simulation options. These additional simulations aim to improve the effectiveness of the total workflow of the method, by comparing those different simulation options to provide a manual for choosing the optimization options.

The effect of changing the number of SPOREs on the quality of the results and on the advanced configuration selection is checked for the configuration solution space. This is done by running the optimising strategy for 50 SPOREs and for 15 SPOREs. Furthermore, the effect of a different

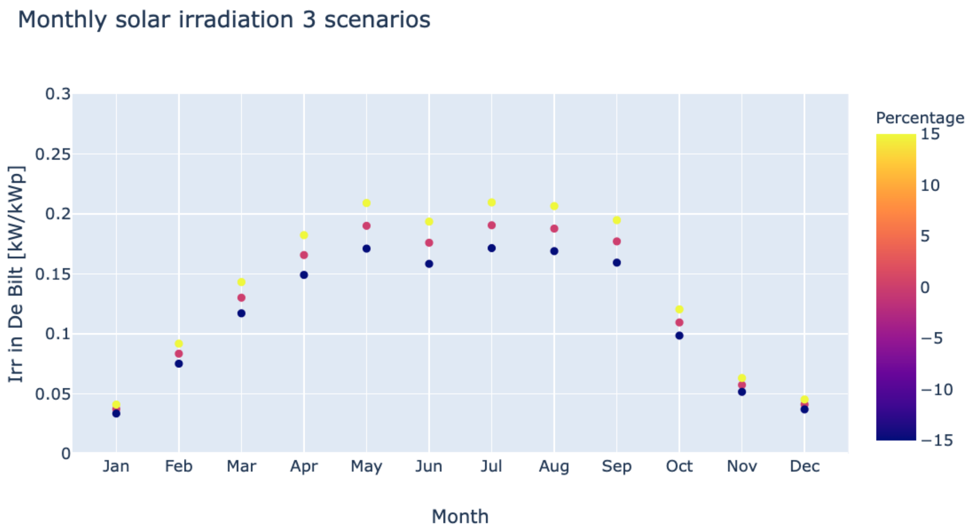

Figure 3.21: An example of Average monthly yield in kW per installed kWp of solar panels, based on location "The Bilt", from the year 2017 [5]. Base case = 0%, sunny case = +15%, cloudy case = -15%. Each case has a 33% probability of occurrence (Appendix C).

slack value on those same results is tested as well for the configuration solution space. This is done by running the optimising strategy for 15% slack and for 50% slack. Lastly, the improved selection method is compared to the cumbersome simple configuration choice approach. All these additional tests are applied to case 2 and their results are discussed in chapter 4.4.

4 Results

The final results of case 1 and 2 are explained in this chapter. First, the results of the method's application on case 1 are visualised. Subsequently, all the case 2 results from the methods' workflow are revealed. Afterwards, an analysis of the additional simulations for slack, number of SPOREs and the configuration selection method is done.

4.1 Case 1

The case 1 results reveal that the required functionalities work as expected. Except for minor hurdles/problems, they also show that most of the workflow can be applied to case 2. Case 1 is used to fine-tune the methodology into the version as explained in section 3.1. An in-depth elaboration on the inputs, assumptions, results, and discussion of case 1, can be found in appendix A. The simulations with a 15% cost slack, 5 SPOREs and 15 different input scenarios are run without the cluster on a private laptop within 12 hours.

4.1.1 Configuration Solution Space

After the optimising strategy, the SPOREs differ in spatial configuration from the optimal solution and other SPOREs as expected. The box-plots show which techniques are essential and which ones are not (see figures 4.1, 4.2, 4.3 & 4.4).

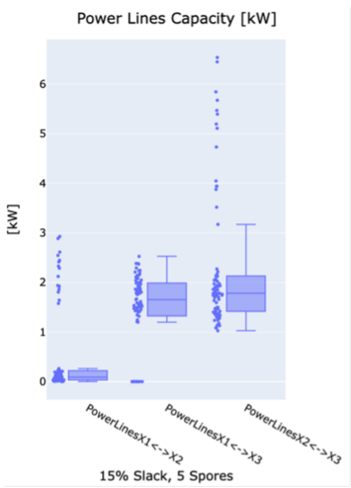

Figure 4.1: Boxplot for the Electricity cable connections between all 3 locations.

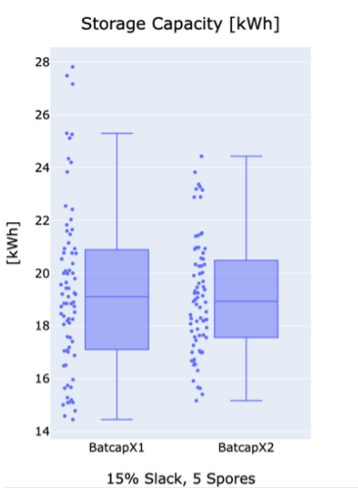

Figure 4.2: Boxplot for the installed battery capacities on locations X1 and X2.

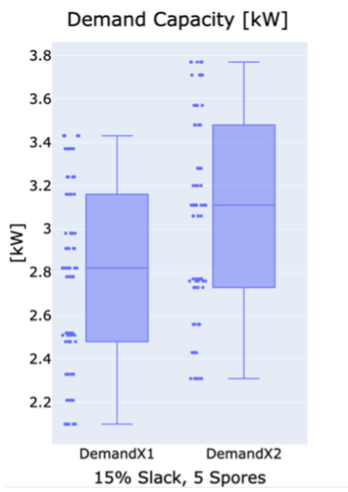

Figure 4.3: The installed electrical demand capacity for locations X1 and X2.

Within the 15% cost slack, the power lines between X2 and X3 seem to be essential, since they have a capacity of at least 1 kW for all solutions (figure 4.1). A similar statement is made for batteries on both locations, as there is always a minimum installed storage capacity of 14 kWh for the complete configuration solution space. This means that the battery technology is essential, on both locations (figure 4.2). For the demand capacity, it is clearly visible and logical that it is directly related to the demand input scenarios. Installing a higher capacity than the maximum demand is pointless (figure 4.3).

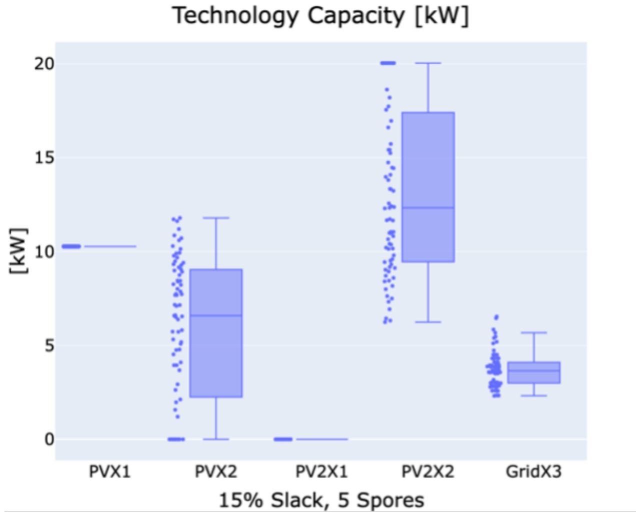

Figure 4.4: Box-plot for the PV and Grid technologies on locations X1 and X2.

Within the 15% cost slack, the installed PV technology (PV type one) on location X1 is fixed for all input scenarios (figure 4.4, in every single solution). For location X2, the distribution of the installed PV types can change, but the roof is always completely covered. This difference can be attributed to the difference in roof inclination. A grid connection is always installed, but its size depends on the highest electrical flow.

Essential takeaways from the configuration solution space:

- **Model relations:** Installed demand capacity is directly related to the demand time-series from the input scenarios. The total installed cable capacity to location X3 must be equal to the maximum PV yield flow. The whole roof area is always used for PV, but the distribution of the PV type fluctuates.
- **(non-) Essential technologies:** The battery is essential for all input scenarios, as well as the electricity cable between X2 and X3. The energy system can also not operate without a grid connection.
- **Certainty range of technologies:** It can be seen that the PV technologies installed on location X2 and the batteries have a large spread in the solution data. This means that these technologies are sensitive to the input scenarios.

4.1.2 Configuration Selection and Testable Configurations

For the remainder of this case, 4 configurations are selected by taking single solutions from the complete configuration solution space (the cumbersome configuration method).

- Configuration 1: Highest battery capacity (input scenario “2008”, solution: “optimal”).
- Configuration 2: Lowest NPV cost (input scenario “2019”, solution “optimal).
- Configuration 3: Highest NPV cost (input scenario “2015”, solution “SPORE 4”).
- Configuration 4: Least CO_2 emission (input scenario “2018”, solution “optimal”).

As mentioned before in chapter 3, the cumbersome method completely ignores many valuable findings from the SPORE method, including recurring technology correlations. The exact capacity values for the selected configuration can be found in Appendix A.

4.1.3 Results

For each of the configurations, the results for the performance indicators cost and CO_2 are compiled in histogram plots (figures 4.5 to 4.12). It can be noted that some configurations are in general cheaper than others. Configuration 2 has on average cheaper results than configuration 1. In the same manner, the CO_2 emissions of configuration 4 are on average much lower than those of configuration 3.

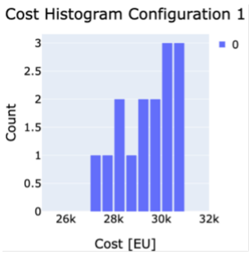

Figure 4.5: Cost histogram Configuration 1.

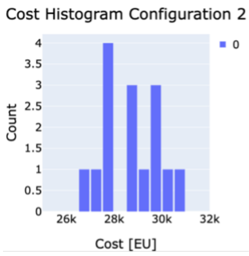

Figure 4.6: Cost histogram Configuration 2.

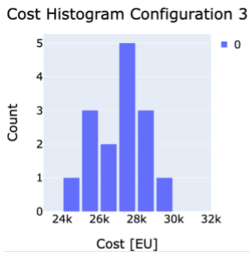

Figure 4.7: Cost histogram Configuration 3.

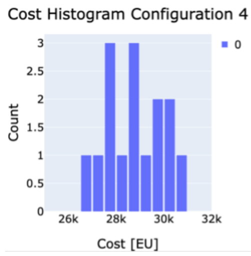

Figure 4.8: Cost histogram Configuration 4.

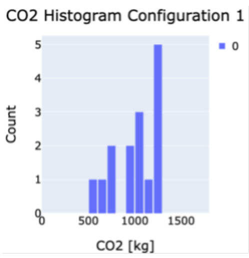

Figure 4.9: CO_2 histogram Configuration 1.

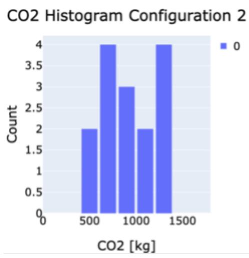

Figure 4.10: CO_2 histogram Configuration 2.

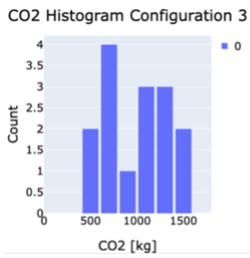

Figure 4.11: CO_2 histogram Configuration 3.

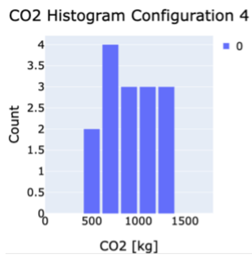

Figure 4.12: CO_2 histogram Configuration 4.

The results of all configurations can be compared by making statistical calculations like the mean value. Those results are summarised in table 4.1.

Table 4.1: Summary results case 1.

Config	CO2 Mean	CO2 Max	Cost Mean	Cost Max	SOS
1	1005	1269	29408	30722	100 %
2	921	1349	28682	30522	99.8%
3	999	1432	27058	29197	99.3%
4	917	1354	28762	30635	100%

From all these results, useful statements can be conducted like “there is an 80% chance to meet a 31k budget when choosing for configuration 1, under the chosen input scenarios". Similar statements can be made for other performance indicators like CO_2 and security of supply.

4.2 Case 2

Each scenario takes about 8-16 hours of simulation time. However, all simulations could be run in parallel within 16 hours thanks to the TU Delft cluster. The case 2 results are based on 15% slack, 50 SPOREs, 27 input scenarios and a 3% interest rate. With 50 SPOREs, the complete configuration solution space consists of 1377 Single solutions. A case 2 results overview can be found in section C.4.

4.2.1 Configuration Solution Space

After the optimising strategy, 27 optimal solutions are conducted, along with 1350 SPOREs. For each scenario, the SPOREs prove to be maximally different from each other, offering good technologically different alternatives in addition to just the optimal one (see figure 4.13 and 4.14).

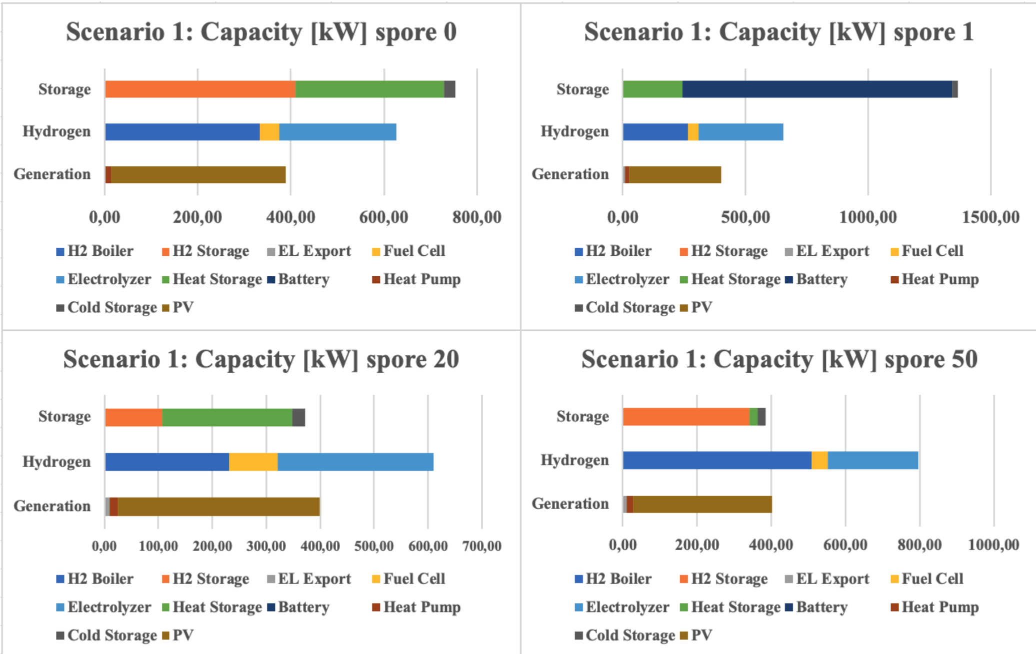

Figure 4.13: Energy capacity distributions for 4 different SPOREs, for input scenario 1.

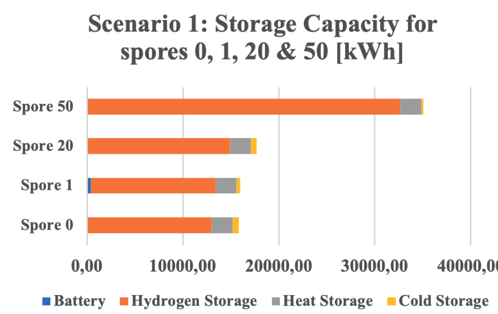

Figure 4.14: Storage capacity distributions for 4 different SPOREs, for input scenario 1.

Each single solution shows expected behaviour. For SPORE 38 (randomly picked as an example where seasonal storage is visible) with input scenario 1, hydrogen storage is installed and used for seasonal storage. In summer, the heat storage gets charged since not much heating is needed then (figure 4.15), while in winter the heat storage is used as short-term storage (figure 4.17). In a summer month (figure 4.16), most electricity is provided by the PV panels, while the excess PV electricity is converted into hydrogen and sometimes even sold back to the grid.

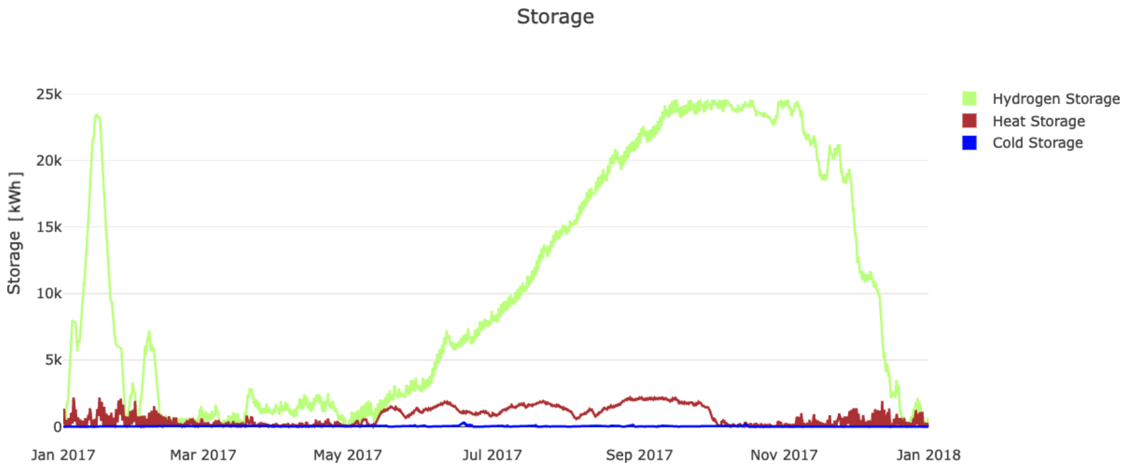

Figure 4.15: Annual storage [kWh] time-series for SPORE 38, for input scenario 1.

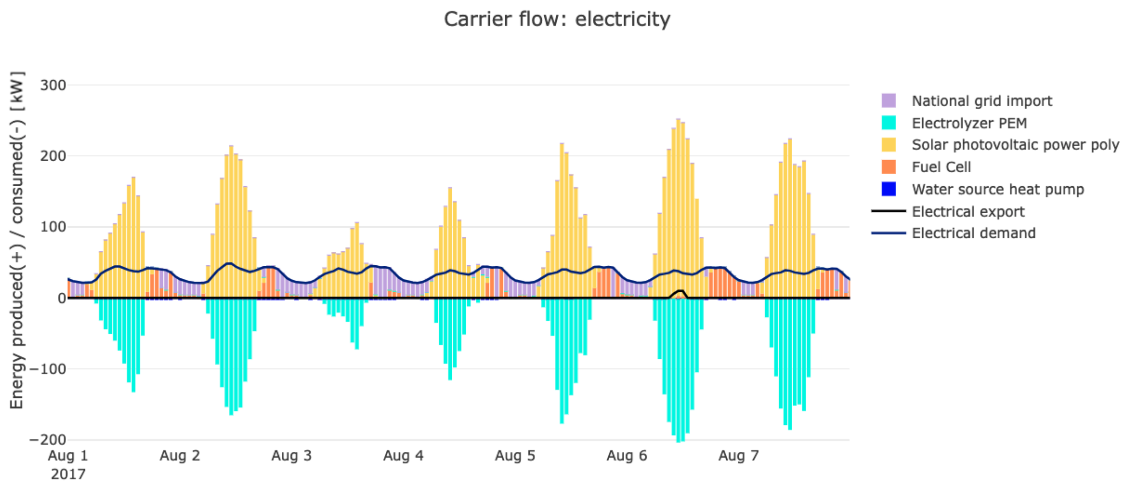

Figure 4.16: Electricity carrier flow [kW] time-series for SPORE 38 during a summer week, for input scenario 1.

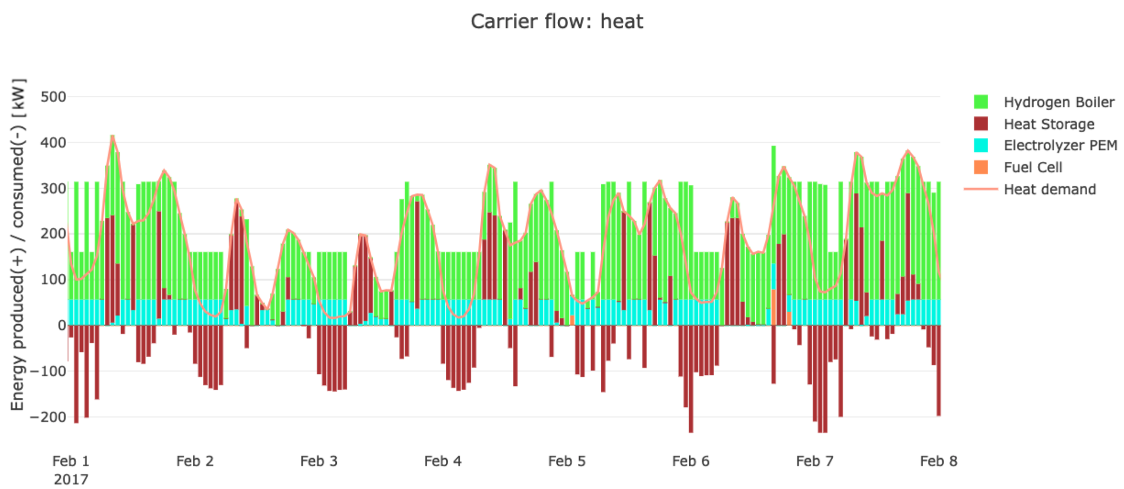

Figure 4.17: Heat storage [kW] time-series for SPORE 38 during a winter week, for input scenario 1.

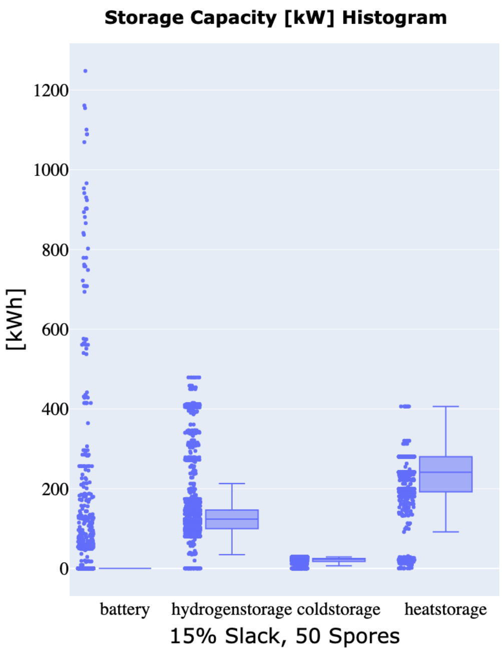

Figure 4.18: Box-plot for the Energy capacity of the Storage technologies for all input scenarios.

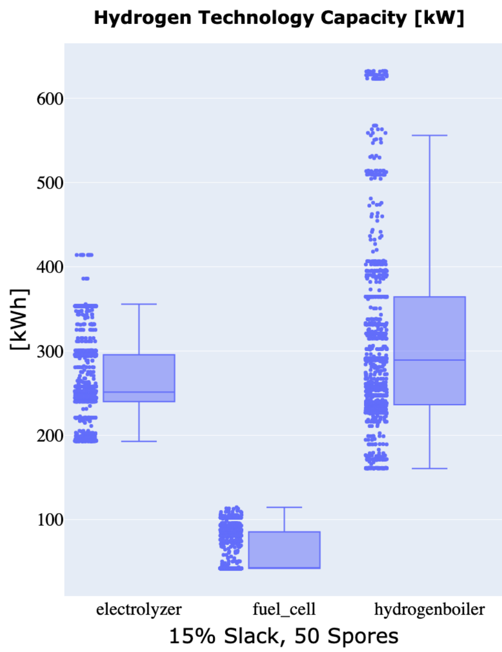

Figure 4.19: Box-plot for the Energy capacity of the Hydrogen technologies for all input scenarios.

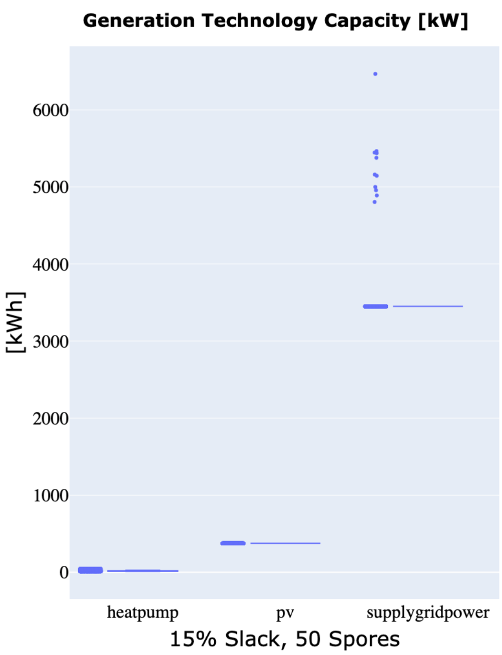

Figure 4.20: Box-plot for the Energy capacity of the Generation technologies for all input scenarios.

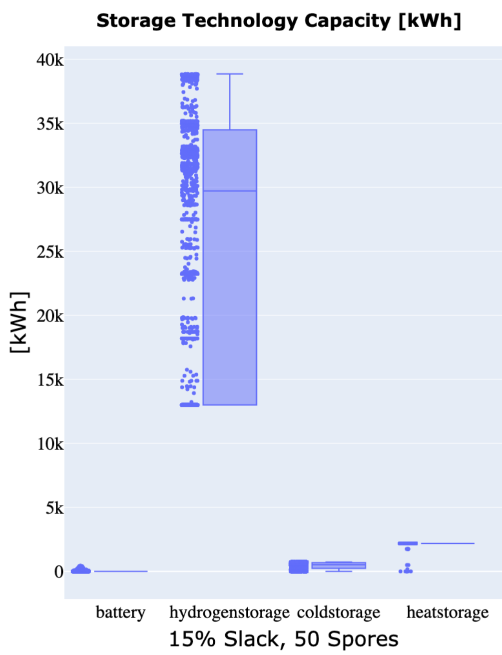

Figure 4.21: Box-plot for the Storage capacity [kWh] of the Storage technologies for all input scenarios.

When plotting the complete configuration solution space in box-plots, several essential takeaways can already visually be concluded (figures 4.18, 4.19, 4.20 & 4.21). These takeaways are sensitive to subjectivity, but can be objectified through the advanced configuration selection:

- **Model relations:** Installed demand capacity is directly related to the demand time-series from the input scenarios. Cooling can only be provided by the heat pump, therefore the heat pump, cold storage and cold demand are connected.

- **(non-) Essential technologies:** Heat storage is almost always at its maximum allowed storage capacity. PV is always at its minimum allowed installed capacity. Battery is almost always zero or very low. The grid capacity is almost always at its minimum.
- **Certainty range of technologies:** The electrolyzer, hydrogen boiler, fuel cell, and hydrogen storage have a large spread in the solution data. This means that these technologies are sensitive to the input scenarios. The PV, grid power, heat storage and battery on the other hand have little to no spread in the solution data, meaning that their capacities are fairly certain.

4.2.2 Configuration Selection

For case 2, the advanced configuration selection method is applied instead of the cumbersome one (see section 3.2). 3 filters (top 10%, bottom 10% and average 10%) are applied for each technology to find structural and repetitive correlations between the technologies that are independent of the input scenarios. For example, when applying a top 10% filter to the storage capacity of hydrogen storage, the resulting capacities look as in figures 4.22, 4.23, 4.24 & 4.25.

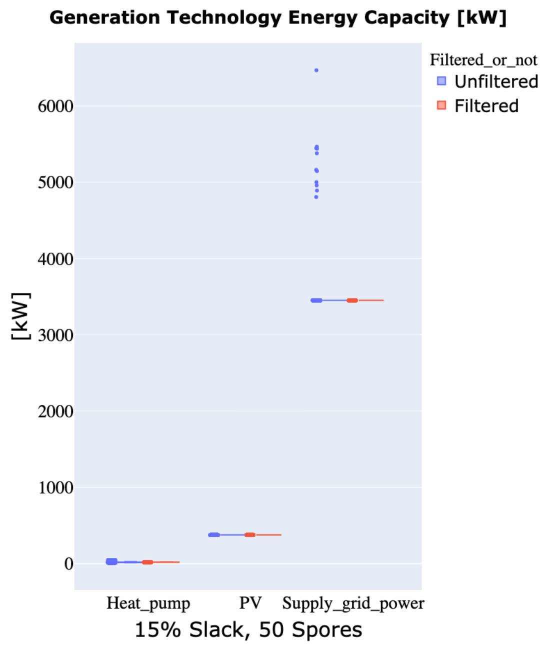

Figure 4.22: Filtered box-plot for the generation technology energy capacity for all input scenarios.

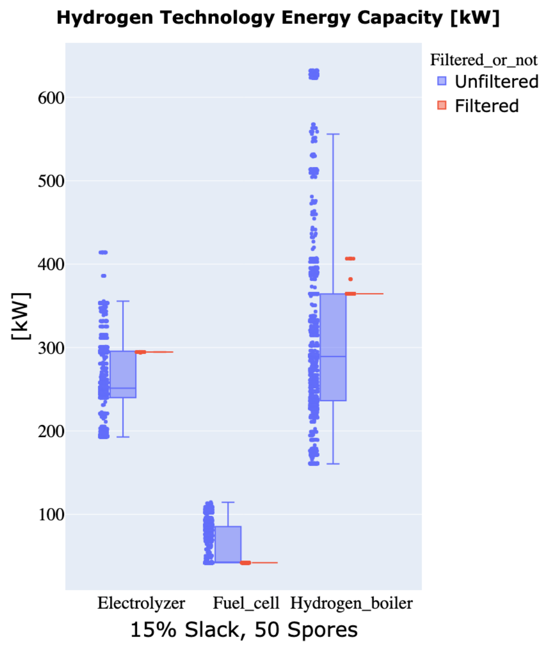

Figure 4.23: Filtered box-plot for the hydrogen technology energy capacity for all input scenarios.

Some technologies show strong correlations with this filter. All the filtered results for heat storage [kWh] (kilo Watt hour), battery [kWh], cold storage [kW] (kilo Watt), battery [kW], fuel cell [kW], electrolyzer [kW], heat pump [kW], PV [kWp] and Grid connection [kW] have a very low spread compared to the unfiltered results. Cold storage [kWh] and hydrogen boiler [kW] still have a spread, but the other correlations can be used and translated to a reliable configuration.

As stated before, some technologies have (almost) no spread, meaning that the configuration filter for the top 10%, bottom 10% and average 10% are unnecessary. For these technologies, all 3 filters result in similar unreliable configurations, making those filters redundant. However, since the process is automised, a total of 52 configurations is automatically created for all 14 technologies (42 for the energy capacity, and 12 for the storage capacity). Eventually, only the configurations where the technology result distributions have a spread will be interesting to compare since many configurations are the same (table 4.2). For now, these "interesting" configurations are chosen manually by only proceeding with the results that are based on filters for the technologies that have a spread. However, this can be automised in the future by only proceeding with the technology/location combinations that have a spread (large enough normalised standard deviation). Ridge plots are created in the next section for the 20 interesting configurations.

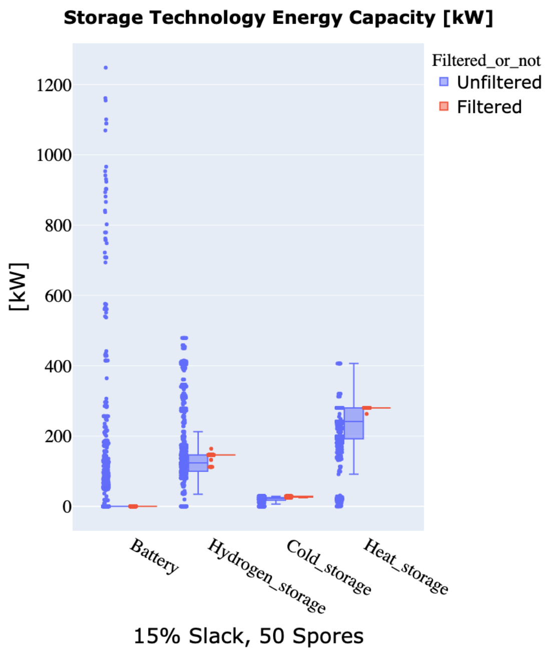

Figure 4.24: Filtered box-plot for the storage technology energy capacity for all input scenarios.

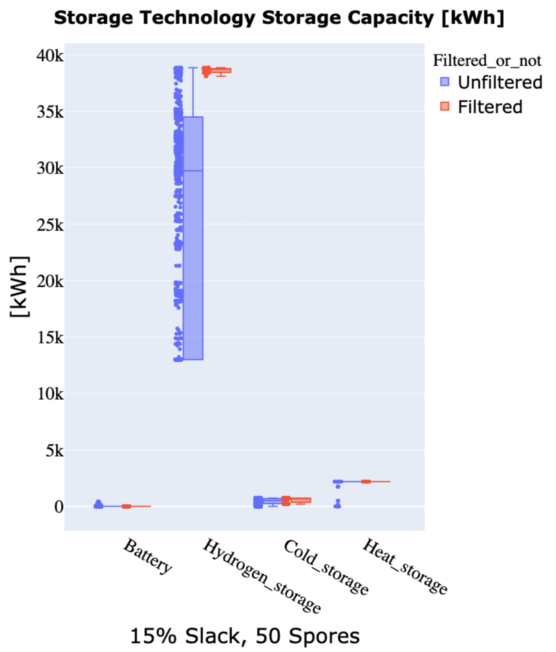

Figure 4.25: Filtered box-plot for the storage technology storage capacity for all input scenarios.

Table 4.2: 20 interesting testable configurations that are tested against performance indicators in ridge plots in the next section. Each interesting testable configuration has its own configuration number (Python index). From the total set of 54 testable configurations, some are duplicates and some are unreliable configurations due to the lack of spread for a certain technology. Therefore, only a set of 20 testable configurations is used to visualise in the ridge-plots in the next section.

Technology	Filter type	Python index	Capacity type
el_export	top 10%	7	energy_cap
el_export	bottom 10%	9	energy_cap
electrolyzer	top 10%	10	energy_cap
electrolyzer	bottom 10%	13	energy_cap
fuel_cell	top 10%	14	energy_cap
fuel_cell	bottom 10%	16	energy_cap
heat_pump	top 10%	17	energy_cap
heat_pump	bottom 10%	19	energy_cap
hydrogen_boiler	top 10%	24	energy_cap
hydrogen_boiler	bottom 10%	26	energy_cap
supply_grid_power	top 10%	34	energy_cap
supply_grid_power	bottom 10%	36	energy_cap
battery	top 10%	37	storage_cap
battery	bottom 10%	39	storage_cap
cold_storage	top 10%	40	storage_cap
cold_storage	bottom 10%	42	storage_cap
heat_storage	top 10%	43	storage_cap
heat_storage	bottom 10%	46	storage_cap
hydrogen_storage	top 10%	47	storage_cap
hydrogen_storage	bottom 10%	49	storage_cap

4.2.3 Results

After creating the testable configurations with the use of the filters, they are tested against all the input scenarios to find out how each testable configuration scores on the chosen performance indicators, total cost, CO_2 emitted, Grid dependency and security of supply. For each configuration, one histogram is created in which a single performance score is visualised against for the input scenarios. For configuration 7 (the top 10% filter for electrical export capacity), the histogram for the cost indicator is visualised in figure 4.26. The cost histogram for configuration 9 (the bottom 10% filter for electrical export capacity) is found in figure 4.27.

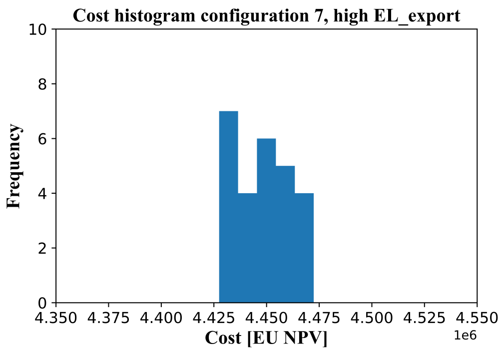

Figure 4.26: Cost histogram for configuration 7 (top 10% filter for high electrical export capacity), against all input scenarios with a mean of 4.45 Million Euros (NPV).

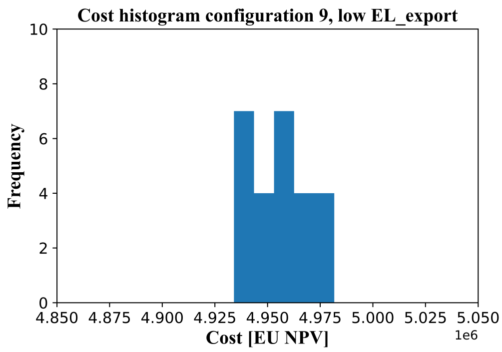

Figure 4.27: Cost histogram for configuration 9 (bottom 10% filter for low electrical export capacity), against all input scenarios with a mean of 4.95 Million Euros (NPV).

All the histogram results per performance indicator for each configuration are summarised simultaneously in the ridge plots, which are found in figures 4.28, 4.30 & 4.29 for the performance indicators total cost, CO_2 emitted and grid dependency. The histograms from figures 4.26 and 4.27 are the first two (7 and 9) histograms in the cost ridge-plot of figure 4.28.

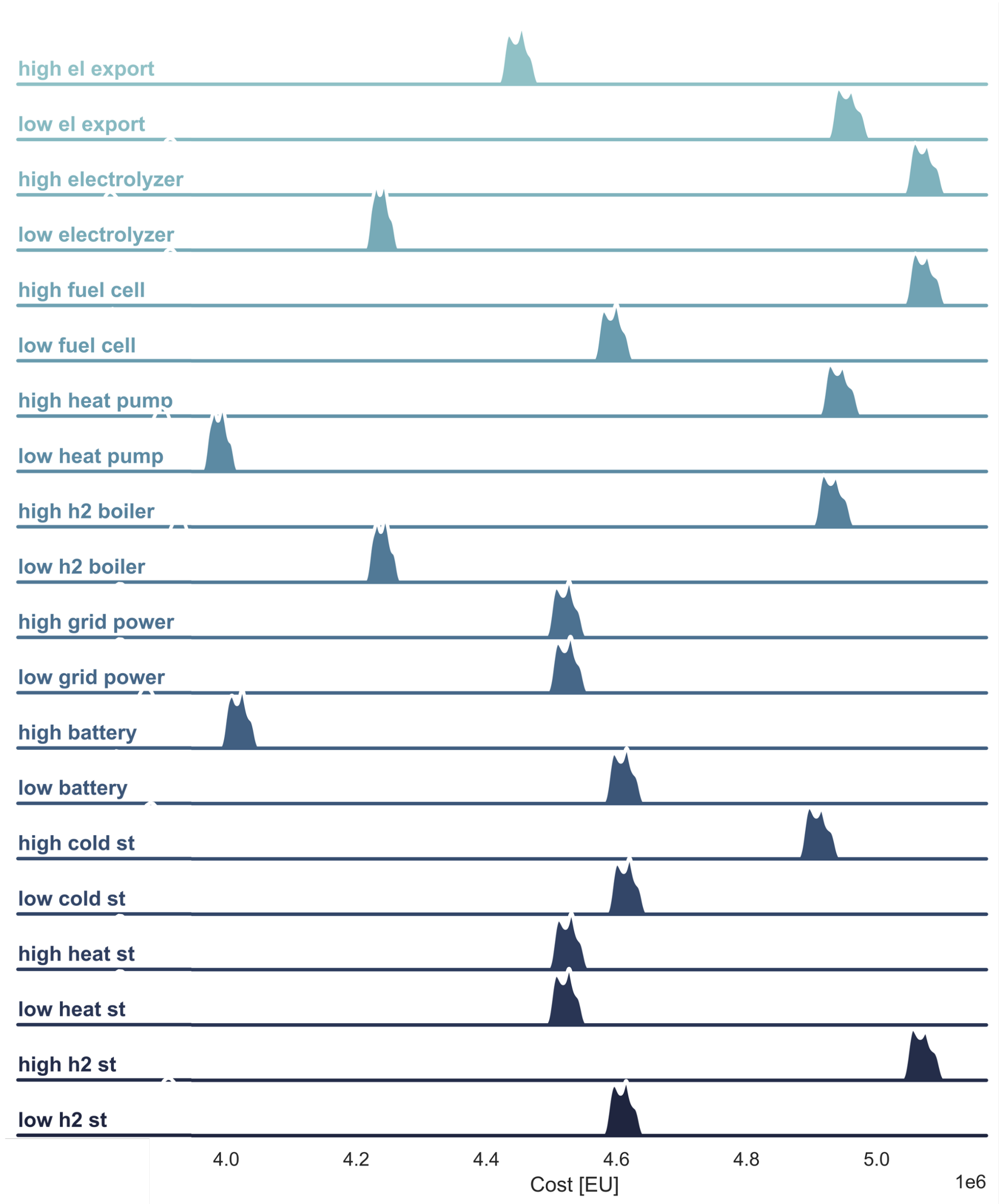

Figure 4.28: Ridge-plot of the cost distribution for only the interesting configurations against all input scenarios for its entire lifetime. St means storage.

When regarding total cost (NPV) as a performance indicator (figure 4.28), it is noted that certain configurations require a higher cost than others. For example, configurations 10 (top 10% electrolyzer energy capacity), 14 (top 10% fuel cell energy capacity) and 47 (top 10% hydrogen storage, storage capacity) show high total cost results for all 27 input scenarios, while configurations 19 (bottom 10% heat pump energy capacity) and 37 (top 10% battery storage capacity) have a much lower cost result. It must be kept in mind that a cheap configuration can go hand in hand with a lower score for the other performance indicators.

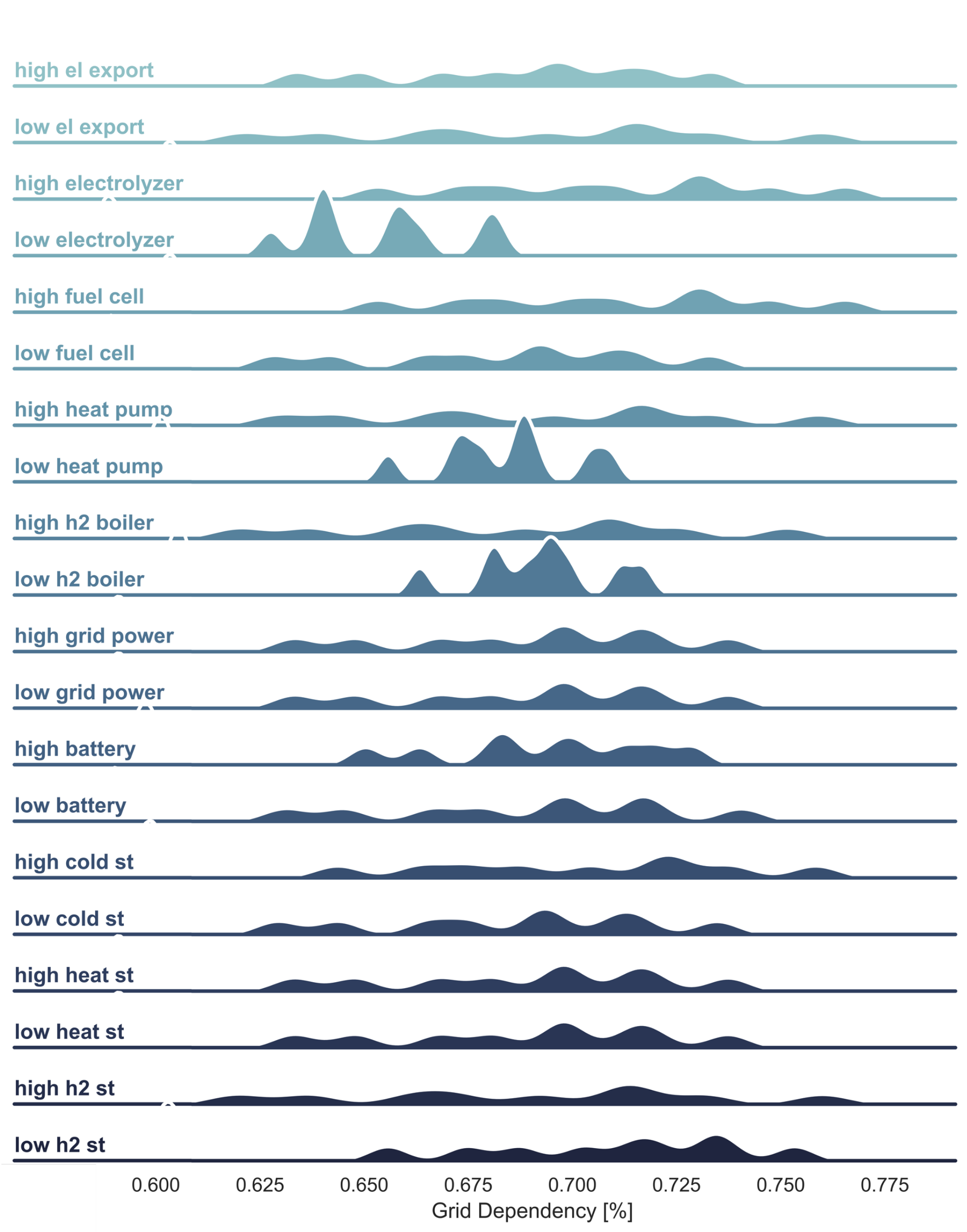

Figure 4.29: Ridge-plot of the grid dependency distribution for only the interesting configurations against all input scenarios. St means storage.

With regard to grid dependency, it is stated that the results are fairly spread out. Nonetheless, the severity of this spread for some configurations is smaller than other configurations and the mean values are much lower than other configurations. For configurations 13 (bottom 10% electrolyzer energy capacity), 19 (bottom 10% heat pump energy capacity) and 26 (bottom 10% hydrogen boiler energy capacity), it is seen that the spread is much lower compared to the other configurations. Despite these differences in spread, it is still possible to find advantages and disadvantages between configurations. For example, a lower grid dependency is imminent for all input scenarios when a low electrolyzer energy capacity is installed. Figure 4.29 also tells us that when a high amount of fuel cell energy capacity is installed (configuration 14), a lot of grid energy is needed to make the energy system feasible.

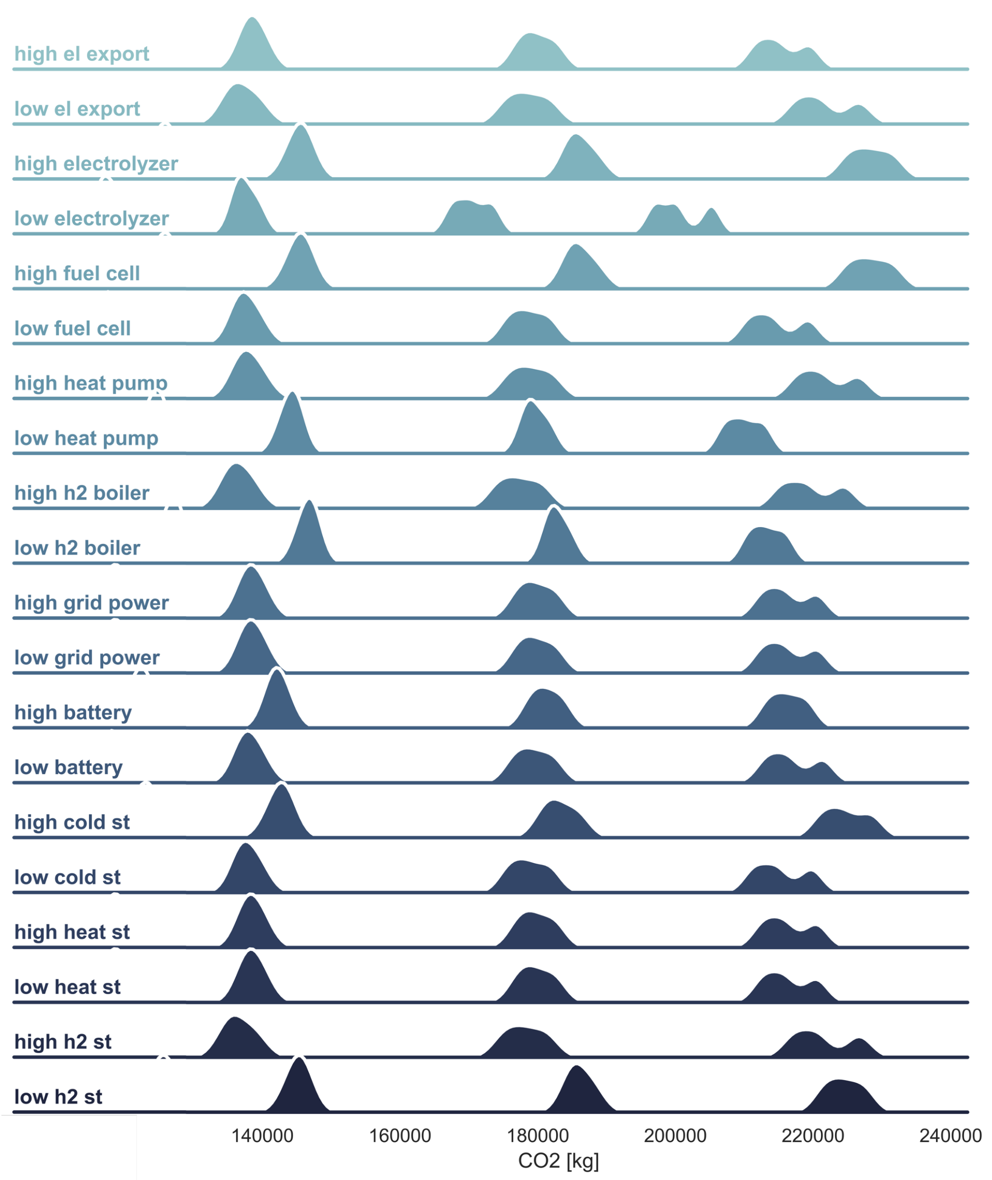

Figure 4.30: Ridge-plot of the CO_2 distribution for the interesting configurations against all input scenarios for its entire lifetime. St means storage.

Regarding the CO_2 performance indicator, it is visible that the results are highly dependent on the input scenarios. Since in 33% of the input scenarios a high demand is simulated, in 33% an average demand, and in 33% a frugal demand, it is expected that three small islands are visible for each configuration in figure 4.30. Ideally, more than just 3 demand input scenarios are used for better analysis that would fill the holes between these "islands" of histograms in the ridge plot. Nonetheless, certain configurations always have a lower CO_2 footprint compared to other configurations. It is clearly visible that configuration 13 (bottom 10% electrolyzer energy capacity) has the lowest CO_2 footprint of all configurations and that either configuration 10 (top 10% electrolyzer energy capacity) or 14 (top 10% fuel cell energy capacity) has the largest CO_2 footprint on average, for all the input scenarios. The SOS ridge-plot is not displayed, but is represented in the next 6 figures (figures 4.31, 4.32, 4.33, 4.34, 4.35 & 4.36) as an additional performance indicator.

Figure 4.31 shows all the mean configurations scores for CO_2 and grid dependency simultaneously. The trend-line fits fairly well to the data, which makes sense since most CO_2 emissions are related

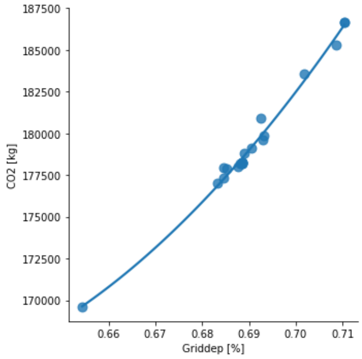

Figure 4.31: CO_2 VS Grid dependency plot.

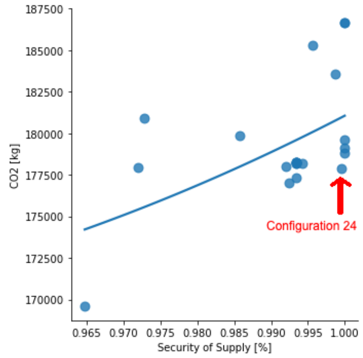

Figure 4.32: CO_2 VS Security of Supply plot.

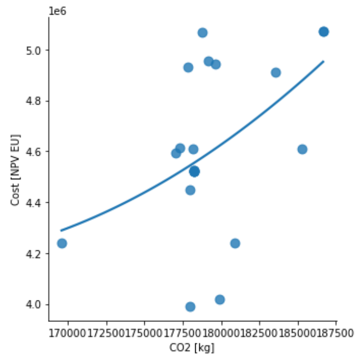

Figure 4.33: CO_2 VS Cost plot.

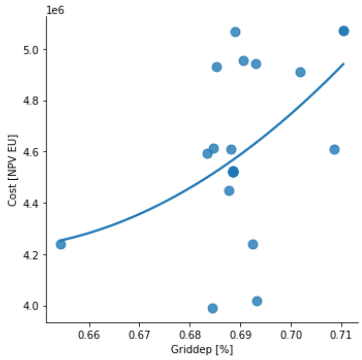

Figure 4.34: Cost VS Grid Dependency plot.

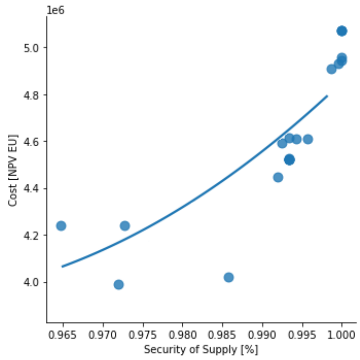

Figure 4.35: Cost VS Security of Supply plot.

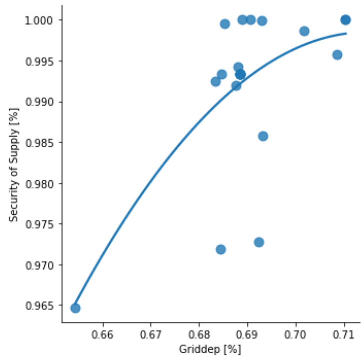

Figure 4.36: Grid dependency VS Security of Supply plot.

to the grid imported electricity (see figure C.1). The other figures can all be used for the decision making process of a project's design phase. For some project designers CO_2 footprint is more important than cost. While SOS is the most important driver for other projects. In addition, three performance indicators can be plotted simultaneously in a 3D plot as well as in figure 4.37).

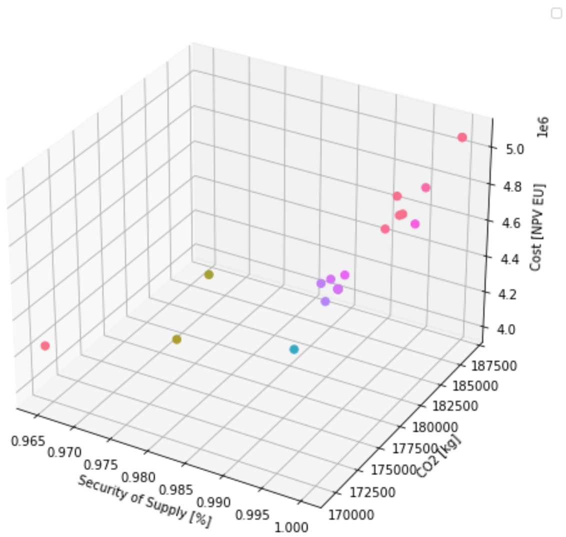

Figure 4.37: 3D plot of Cost, CO_2 and security of supply.

4.3 Finalised Design Advice

If for example a project designer's main design drivers are to reduce the CO_2 emissions while maintaining a high security of supply, figure 4.32 is used to select the best configuration according to the designers preference. The configurations on the right side of the figure all have a similarly high SOS, but a different CO_2 score. In this case, Configuration 24 (top 10% hydrogen boiler energy capacity) is one of the better options since it reduces the CO_2 emissions while maintaining a 0.999 SOS. From the configuration selection method, the testable configuration 24 is selected and used as design advice for the project. The retrieved component capacities from the advanced configuration selection method can be seen in figures 4.38 and 4.39.

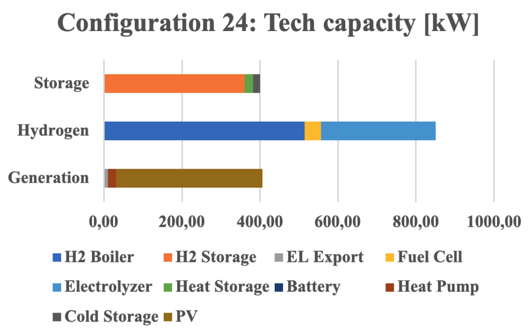

Figure 4.38: Energy capacities for technologies for configuration 24.

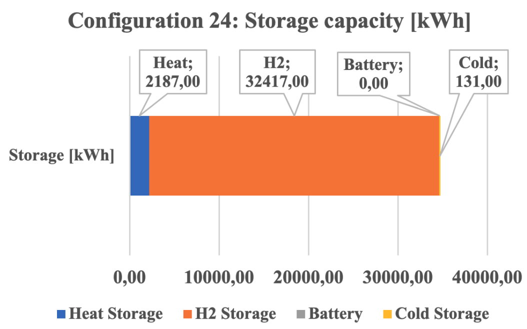

Figure 4.39: Storage capacities for technologies for configuration 24.

It is also possible to create an overview of the statistical results in a table. In table 4.3, all ridge-plot results are described through their mean values and standard deviations (STD). A designer can then apply decision drivers simultaneously and directly see the trade-offs between them.

Technology	Filter type	Configuration	Mean cost	STD cost	Mean SOS	STD SOS	Mean co2	STD co2	Mean grid dep.	STD grid dep.
El export	top 10%	7	4448170	13474	0,992	0,011	177977	32015	0,688	0,032
El export	bottom 10%	9	4955258	14359	1,000	0,000	179140	35346	0,691	0,043
Electrolyzer	top 10%	10	5071707	14136	1,000	0,000	186654	34493	0,710	0,035
Electrolyzer	bottom 10%	13	4237935	11065	0,965	0,030	169602	26433	0,654	0,018
Fuel cell	top 10%	14	5072035	14136	1,000	0,000	186656	34492	0,710	0,035
Fuel cell	bottom 10%	16	4593889	13448	0,992	0,011	177018	32172	0,683	0,033
Heat pump	top 10%	17	4941880	14274	1,000	0,000	179609	34994	0,693	0,041
Heat pump	bottom 10%	19	3989249	11712	0,972	0,026	177940	27443	0,684	0,016
H2 boiler	top 10%	24	4931633	14056	1,000	0,001	177858	34677	0,685	0,041
H2 boiler	bottom 10%	26	4239636	11798	0,973	0,026	180925	27790	0,692	0,016
Grid power	top 10%	34	4521092	13591	0,993	0,010	178227	32468	0,689	0,033
Grid power	bottom 10%	36	4523299	13592	0,993	0,010	178221	32473	0,688	0,033
Battery	top 10%	37	4018884	12977	0,986	0,014	179880	30844	0,693	0,025
Battery	bottom 10%	39	4609744	13690	0,994	0,008	178191	32897	0,688	0,034
Cold storage	top 10%	40	4909416	14135	0,999	0,002	183557	34212	0,702	0,036
Cold storage	bottom 10%	42	4614118	13521	0,993	0,010	177327	32320	0,685	0,033
Heat storage	top 10%	43	4524623	13592	0,993	0,010	178216	32472	0,688	0,033
Heat storage	bottom 10%	46	4521092	13591	0,993	0,010	178227	32468	0,689	0,033
H2 storage	top 10%	47	5069456	14345	1,000	0,000	178798	35436	0,689	0,044
H2 storage	bottom 10%	49	4608950	13767	0,996	0,006	185276	33012	0,709	0,030
		Unit:	[EU]	[EU]	[%]	[%]	[kg CO2]	[kg CO2]	[%]	[%]

Table 4.3: Overview of statistical data for all interesting configurations. the mean and STD values for cost, SOS, CO_2 and grid dependency are displayed.

The structural uncertainty can now more easily be addressed by filtering the testable configurations to those that meet the additional design criteria. For example, if the installed cold storage capacity is preferably low due to a personal preference or due to an upcoming subsidy, the effects of that preference to the performance indicators can directly be found in the summarised statistics table.

When using the conventional SPOREs method (without MCS), one only considers one input scenario, resulting in only viable cost effective spatially different solutions for one future outcome. These results however, only show spatially different configurations that work very well for multiple uncertain scenarios, making the results more robust against uncertain futures.

Compared to using only MCS, this method is much more efficient as it only provides results that work very well for the input scenarios (thanks to the optimising steps). Furthermore, the sub optimal solutions are used as well in conducting the testable scenarios, automatically providing multiple other design criteria without the need to define those through human input in the scenario definition.

4.4 Additional Simulations

Additional simulations have been run to see the effect of different SPOREs and slack values on the results.

4.4.1 15 VS 50 SPOREs & 15% Slack VS 50% Slack

The effect of simulating a different number of SPOREs (15 and 50), while keeping the slack value constant is only fairly visible. The main spreads and ranges of both results are very similar and comparable, which can mean that a fewer number of SPOREs (lower computational power) is enough to find similar results. However, it can still be argued that when an energy system is complex (many technologies and spatial locations), a similar spread might not be enough to map all possible maximally different spatial solutions. Therefore, a higher number of SPOREs is preferred for those complex energy systems. Nonetheless, a valid statement about the perfect number of SPOREs, for a specific energy system can not be conducted from these results. The results only show that additional research is required if the computational time for these calculations is to be optimised.

However, changing the slack value does present a clear difference in results. As expected, a higher slack results in a larger spread for the uncertain technologies. A higher amount of capacity can be purchased with a larger budget, resulting in even more spatially different (varying capacity distributions between multiple nodes with similar technologies) solutions compared to a lower slack value. As further discussed in chapter 5, this does not mean that a higher slack value should always be used for this method. The slack value should strongly depend on what phase the project is in and if a larger budget for the project is available or not.

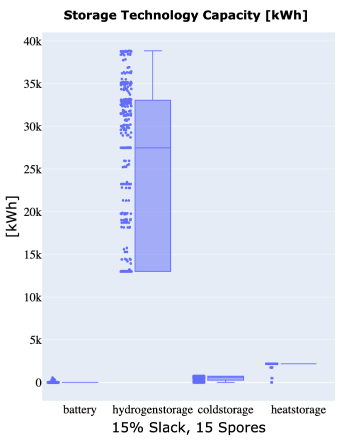

Figure 4.40: Box-plot for the Storage capacity [kWh] for all storage technologies with all input scenarios at 15% slack and 15 SPOREs.

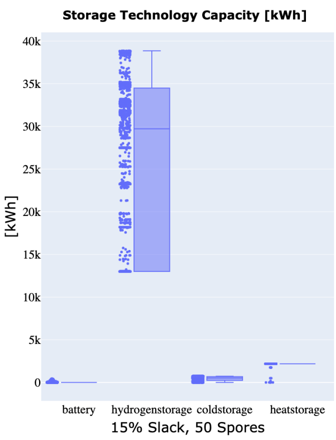

Figure 4.41: Box-plot for the Storage capacity [kWh] for all storage technologies with all input scenarios at 15% slack and 50 SPOREs.

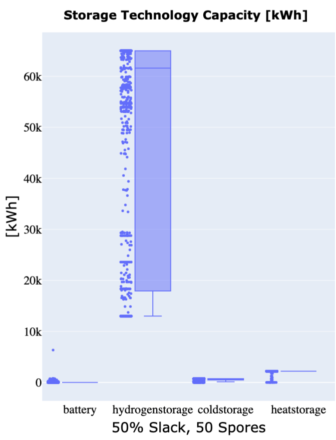

Figure 4.42: Box-plot for the Storage capacity [kWh] for all storage technologies with all input scenarios at 50% slack and 50 SPOREs.

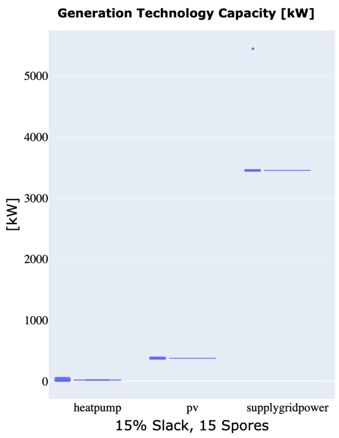

Figure 4.43: Box-plot for the Energy capacity [kW] for all generation technologies with all input scenarios at 15% slack and 15 SPOREs.

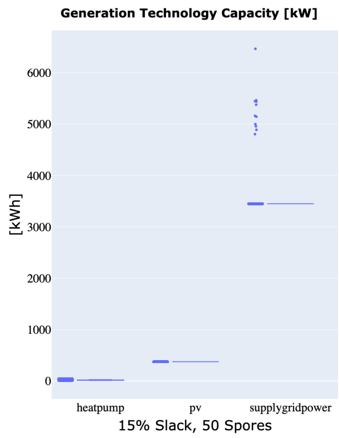

Figure 4.44: Box-plot for the Energy capacity [kW] for all generation technologies with all input scenarios at 15% slack and 50 SPOREs.

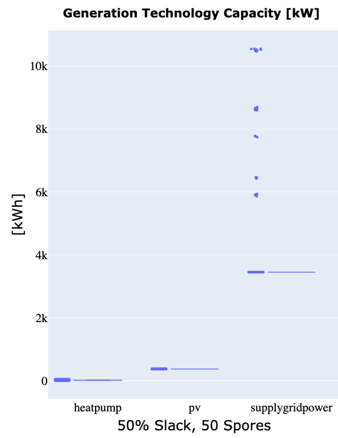

Figure 4.45: Box-plot for the Energy capacity [kW] for all generation technologies with all input scenarios at 50% slack and 50 SPOREs.

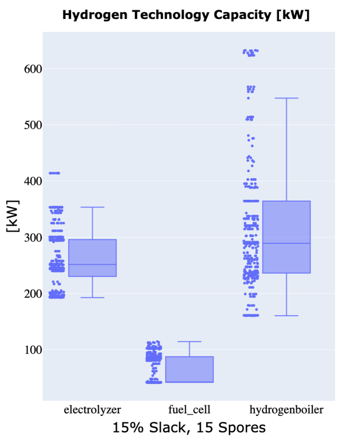

Figure 4.46: Boxplot for the Energy capacity [kW] for all hydrogen technologies with all input scenarios at 15% slack and 15 SPOREs.

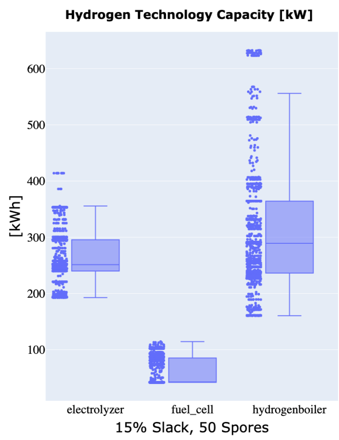

Figure 4.47: Boxplot for the Energy capacity [kW] for all hydrogen technologies with all input scenarios at 15% slack and 50 SPOREs.

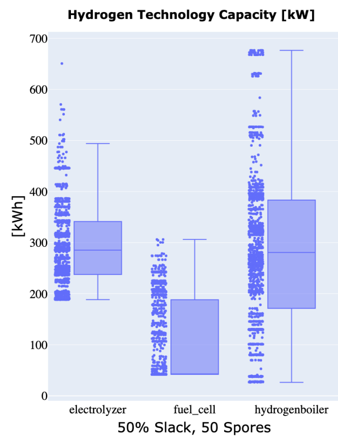

Figure 4.48: Boxplot for the Energy capacity [kW] for all hydrogen technologies with all input scenarios at 50% slack and 50 SPOREs.

4.4.2 Advanced Configuration Selection Method

As visualised in the beginning of section 3.3, the advanced configuration selection method is used successfully for case 2. Figures 4.22, 4.23, 4.24 & 4.25 show how a single filter is applied to the complete configuration solution space. This approach is much more viable compared to the cumbersome configuration selection method that was used for case 1. This method provides a structured and automatised way to check the effects of changing each technology-location combination for a top 10%, average 10% and bottom 10% capacity, making it much more reliable than simple selecting single solutions from the configuration solution space.

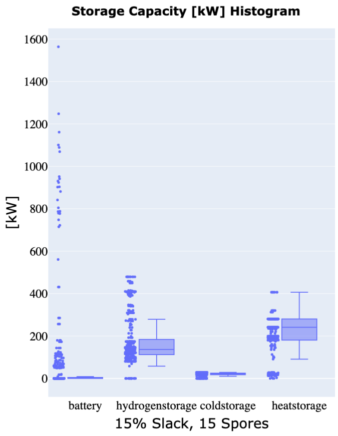

Figure 4.49: Boxplot for the Energy capacity [kW] for all storage technologies with all input scenarios at 15% slack and 15 SPOREs.

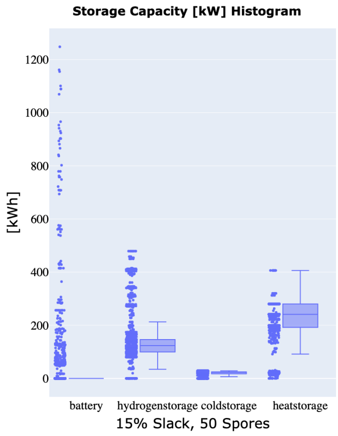

Figure 4.50: Boxplot for the Energy capacity [kW] for all storage technologies with all input scenarios at 15% slack and 50 SPOREs.

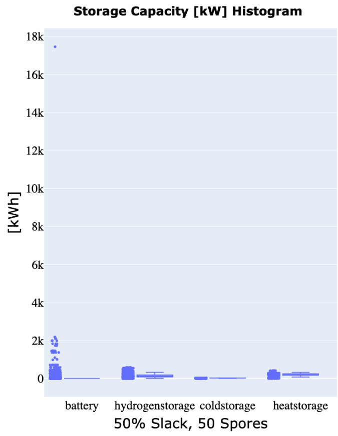

Figure 4.51: Boxplot for the Energy capacity [kW] for all storage technologies with all input scenarios at 50% slack and 50 SPOREs.

5 Discussion

5.1 Study Objectives and Key Findings

The case 1 results reveal that the required functionalities work as expected, and except for minor problems, they also show that most of the workflow could be applied to case 2. Case 1 is used to fine tune the methodology into the version as explained in chapter 3. The case 2 results show that the study objectives are successfully obtained with the proposed method. It shows the potential to be a reliable insightful method for energy system design that provides useful findings which are crucial in deciding the best final energy system composition.

5.2 Method Application

A dependency check is included to verify if the resulting filtered data is not too dependent on the input scenarios in the advanced configuration selection method. This step is reasonable and necessary since a high capacity of (for example) wind power can strongly depend on an input scenario where a lot of wind occurs, implying that installing more wind power is much more useful than a different energy source for that input scenario. This is in that case not a correlation of the technologies within the energy system itself, but a direct correlation of the high wind production and wind power capacity. Since the goal of the advanced configuration selection method is to find energy system specific correlations, it is not useful if the filter analyses configurations that only have a direct correlation to the inputs. This is currently conducted automatically in the dependency check, based on an arbitrarily chosen value of 25% dependency. This value can be improved by replacing it with one based on literature.

The simulations for this thesis are conducted on a TU Delft student account on the high computing power (HPC) cluster. This student account has a standard available disk space of 15 GB on the cluster. The method results are compressed into netCDF files with Calliope's functionality for this thesis, resulting in a maximum required disk space of about 5 GB. These netCDF results are moved to a laptop and translated into CSV files that are required to calculate the performance indicators. A larger available storage capacity is recommended for more complex future projects that include more or better uncertain variables.

With the current settings and cluster availability, the case 2 calculations are conducted within 16 hours by running all 27 scenarios in parallel. Each input scenario then takes up to 16 hours to conduct its optimal solution and the 50 sub optimal solutions. As of this day, Francesco Lombardi (main developer of SPOREs) is also working on an improved SPORE version that allows the SPORE calculations to be executed in parallel. When finished, this improvement can greatly reduce the calculation time for these energy system problems, making the method even more promising with regards to high computational computing.

Two different simulations are conducted with a different number of SPOREs for case 2. The difference in results (see section 4.4.1) is not large as the spreads are similar for both simulations, meaning that 15 SPOREs seems to provide enough distributed results for this energy system. However, the drawback for a reduced number of spores is that they might not provide enough solutions for identifying all possible different configuration solutions. The current number of SPOREs (50) is chosen arbitrarily, but can be calculated automatically by finding a correlation between the complexity of the energy system (number of technology/location combinations) and the variability of them in the results. By finding the number of active constraints and technologies of the energy system, this correlation could be found. Additional simulations and research to verify this automatised calculation for the best number of SPOREs is recommended.

A similar statement is made about the currently arbitrarily chosen SPORE slack value. A large spread and maximally different capacity distributions are available in the results with the 15% slack value, resulting in valuable insights thanks to the increased budget. A larger spread in the results is visible (see section 4.4.1) with the additional simulation of 50% cost slack, providing additional insight in component sensitivity. Choosing the best slack value for a project is dependent on project criteria, but running for multiple slack values can always provide additional insight in the trade-offs between money and other decision drivers, making running for multiple slack values as a standard an attractive option.

Many literature-based assumptions are made for the component characteristics for case 1 and 2, resulting in a realistic digital energy model compared to one that is based on simplified assumptions. However, the components can be made even more realistic by finding the best way to represent a digital version of it. For example, some components are modelled as if they don't produce any CO_2 during the production process, and some component prices or interest rates are based on (price) ranges. By providing more realistic values, the energy model can be made even more realistic.

Operation strategies is a challenging subject to address, as they will always be a drawback within optimization. Optimization always calculates the best dispatch, despite any preference of energy usage. In case a designer prefers to charge the battery first with excess solar production before sending it to an electrolyzer or selling it to the grid, the optimization will completely ignore this preference if the optimal solution is otherwise (which can be the case if battery storage has a lower levelised cost of energy (LCOE), compared to selling electricity to the grid). Some strategies can be implemented in optimization by adding additional constraints, but not all of them. However, this is a general optimization problem that is not within the scope of this thesis to consider thoroughly.

The computational power of computers is increasing, and will keep doing so in the future. The optimization is currently done with data-sets of hourly resolution, that oversee aspects like ramp up time and peak usage. Energy system modelling can be made even more realistic if they are analysed for their real-time data with a higher resolution, which will be feasible eventually in the near future with the increasing computational power.

In the advanced configuration selection method, each technology/location combination is filtered 3 times to obtain its top 10%, bottom 10% and average 10% capacity solutions. This results in a valuable set of testable configurations that are tested further on in the evaluation. However, many solutions are inter correlated between certain technologies, resulting in similar configurations that occur more than once. The advanced configuration selection method can therefore be even further improved by automatically filtering out all repetitive configurations from the resulting configurations. This could also be prevented earlier in the process by including some sort of sensitivity analysis of the technology-location combinations, before creating all the filtered results.

Moreover, a focus can be applied within the advanced configuration selection method if the main decision should depend on just a few technologies (given as input). The advanced configuration method can then look at those technology-location combinations with a higher resolution, ignoring the other technology-location combinations. If for example hydrogen storage is an interesting factor for a client, this could mean that more than just 3 filters can be applied to this technology (for example the top 5%, the ¾ 5%, the avg 5%, the ¼ 5%, and bottom 5%). Then, a more in-depth analysis will be done on the technology-location combination that is of most interest to the designer or client.

All the configurations are tested against all the input parameters in the evaluation phase. This is currently done with the "plan" mode of Calliope. However, when using Calliope's plan mode, perfect forecast of the inputs is considered which is unrealistic in practice. A shorter forecast window is considered every day (24 hours) when using operate mode, where the input parameters of only the next few days (48 hours) are considered instead of the entire year. This is more realistic since in practice energy systems don't make decisions based on the next year, but more likely on the next few days by taking weather forecasts into account. Before deciding to use plan mode for the evaluation phase, the operate mode has been attempted. Unfortunately, operation mode is currently not maintained as much within Calliope as plan mode, leading to bugs for some specific model configurations, often involving storage technologies. However, it is expected that this problem is resolved in the next major release of Calliope, which is coming soon. Operate mode is preferred for future more realistic operations, despite possibly losing insight in the seasonal storage solutions.

All the correlations within the energy system are automatically accounted for through the advanced configuration method, resulting in testable configurations that are tested in the evaluation phase. Despite all being accounted for, these correlations are not made visible with the final results. They can however be extracted by looking at the intermediate results in the configuration selection phase. These intermediate results help understand the essential operation features of an energy system.

5.3 Scientific Impact and Practical Applications

As requested in the introduction of this thesis, the combined method combines the strengths of optimization modelling and scenario modelling. It provides a structured approach that can provide valuable design insights about the energy system that is addressed.

What makes this method so universal is its ability to choose between using all or just a selection of its functionalities. This method provides the possibility to include parametric uncertainty by defining multiple scenarios (MCS) with different future outcomes. It can include energy systems with multiple spatial nodes by defining them in the energy system configuration. It can also use sub optimal solutions to address more structural uncertainty by allowing more than 0 SPOREs. The method can also find relevant and interesting testable configurations automatically by applying the advanced configuration selection method instead of the cumbersome configuration selection method. All of these functionalities can, but don't have to be used when the designer is less interested in the use of one of them.

Furthermore, this method can be applied to a wide variety of energy system types. As long as the energy systems' possible components, their technical aspects and their allowed interactions are known beforehand, the energy system can be analysed with this method. The allowed energy system is also not limited to specific energy carriers, as they can be defined by hand in Calliope manually.

6 Conclusion

6.1 Answers to Research Questions

To reflect back on the main purposes of the thesis, the aim to create a method that can address parametric and structural uncertainty simultaneously is by all means achieved. This thesis shows that two methods can successfully be combined into one concise method, while providing relevant and valuable insights that can be used for design phases in energy systems. The research questions, as proposed in chapter 1 are answered in this chapter as well:

How can intermittent energy system models provide reliable insights for optimised energy system designs by systematically including both structural and parametric uncertainties?

1. Which variables are most relevant to model as uncertain in the ESM?
2. How can these uncertain variables be modelled in a reliable and accurate way to be used as inputs for the combined method?
3. Which methods are effective in addressing parametric and structural uncertainty in ESOM and which ones are most suitable for this thesis?
4. How can the most suitable methods be systematically combined into a single method?
5. Can applying the method to one or two intermittent and renewable case studies (im)prove its effectiveness and does it improve energy system design?
6. What kind of useful insights can this method provide when applied to one or two W+B cases regarding effective energy system design?
7. How can the method be made easily accessible for other future energy system design projects?

The most relevant and commonly modelled uncertain variables in ESM (1) are solar yield, wind yield, demand, and prices (read more in section 2.5, table 2.2). These uncertain variables are commonly modelled (2) by taking Monte Carlo scenario samples through Weibull distributions (for wind), the ARMA technique (for wind), the TPLF method (for solar) and by reusing historic data (read more in sections 2.2 & 2.5). MCS, SO and RO are the most broadly methods used to address (3) parametric uncertainty in ESM (read more in section 2.2), while MGA and SPOREs are great ESM methods to address structural uncertainty (read more in section 2.3). For this thesis, the combination of both MCS and SPOREs are most suitable in regards to the design of energy systems. The methods are combined (4) into an effective method by running SPOREs optimization for multiple Monte Carlo scenarios (read more in chapter 3).

When applying the method (5) to two case studies (case 1 and case 2), promising output results are found that can be used for improved design purposes. These results entail (6) histograms, ridge plots and statistical values (read more in chapter 4) that summarise the performances for all configurations effectively, making the benefits and disadvantages of each technology trade-off very clear. Case 2 is relevant to one of W+B's current projects and its results can directly be used for further evaluation and improvement of the project design (read more in section 4.3). The approach that has been used can be applied to different inputs (7) and energy systems by feeding different data to the framework.

6.2 General Conclusion

The study objectives are successfully obtained with the proposed method. It shows the potential to be a reliable insightful method for energy system design. This method provides the insights to find (non)-essential technologies, and quantifies the monetary trade-offs in deciding between technology/location capacities, just like when only using the SPORE method. It clarifies the possible decision space that can provide solutions (political and socially motivated) other than the cheapest one, but all with the possibility to include uncertain inputs.

The proposed method can be seen as a vital tool to help speed up the decarbonization process for energy systems since it also concludes uncertain input parameters. Since many aspects of the future energy systems are uncertain, this addition is essential to make energy system design inclusive. It can and should be used by all energy system designers that have uncertain features and can be implemented into the Calliope framework as a new method (next to the current plan, operate and SPORE modes) and turned on if relevant.

The method is highly recommended for energy systems that are complex and too hard to solve analytically. It provides insights that are worth the computational time since many problems can be solved beforehand by modelling the energy system properly with this method.

6.3 Recommendations for Further Research

The cases that are used for this thesis represent the methods effectiveness in a broad manner. In this thesis the method is tested on simplified energy systems in case 1 and case 2, showing a high effectiveness when applied to energy systems that are subject to uncertainty. However, the method's effectiveness can still be tested for different cases as well:

- **More uncertain variables:** In reality, more than 3 variables can be uncertain. The method's performance can be tested for energy systems with more than 3 uncertain variables.
- **Better representation of the uncertain variables:** For case 1 and 2, a simplified approach is used to create uncertain input scenarios. Energy systems with more realistic uncertain variables should also be analysed with this method.
- **Larger sample size:** Creating more realistic scenarios from uncertain variables can be achieved by taking more samples from the uncertain variable.
- **Energy system spatial configuration (inputs):** In case 2, only one spatial location is considered, while in reality the energy system is much more complex. Testing the method on the same system with and without spatial resolution can provide different results and different computational times (see figure 6.1).
- **Different temporal resolution:** Currently, the model is run for hourly data. But using a longer time scale (like for example 2, 4 or 6 hours) can also produce similar results while reducing the computational time significantly. Therefore testing the method on both resolutions will provide insight in the trade-offs between computational time and temporal resolution.

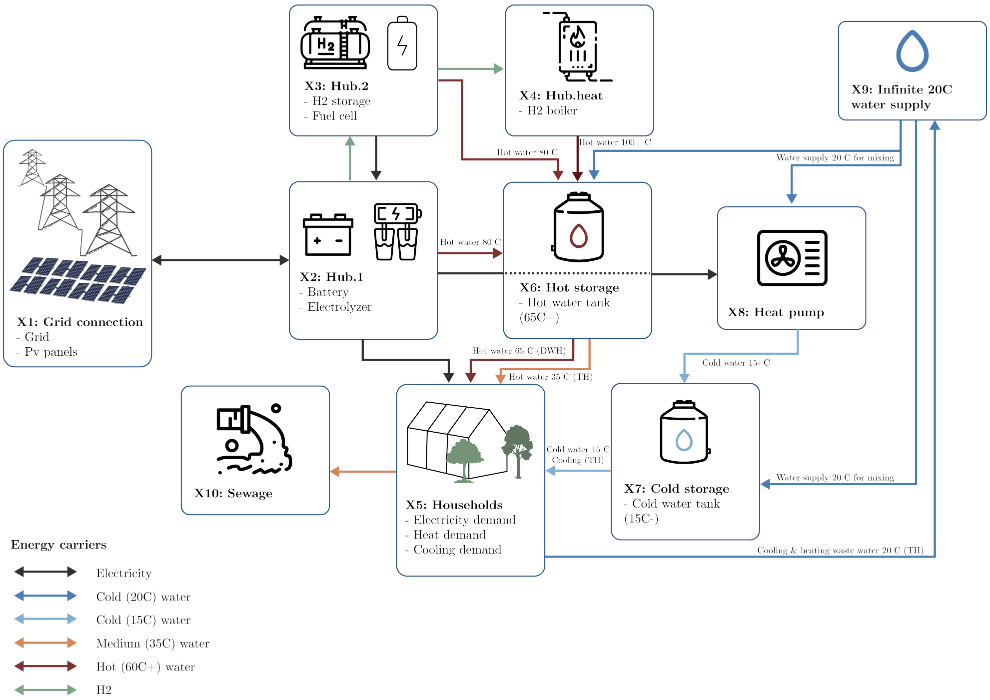

Figure 6.1: An advanced version of the spatial configuration of case 2.

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A | Case 1 Continued

To briefly test what Calliope can do in the context of this thesis, a relatively simple test case will be defined and tested in combination with both uncertainty methods. This test case will be used to see how the combined method reacts to different inputs and if it can provide relevant insights for the continuation of this thesis. The chosen test case will be modeled in a way that the following aspects can be analyzed: - Transmission losses - Battery losses (roundtrip and self-discharge) - The impact of high and low demand on different locations - Choosing between two PV types with different efficiencies, when installed in two possible inclinations. - The impact of different demand profiles - The impact of different solar profiles. As said before, the aim of this thesis is not to be able to model (uncertain) aspects in the most perfect way, but to be able to assess them in the best way, provided they are correct. Therefore, for this test case, many assumptions have been made, based on current day values and reasonable estimates. The remainder of this chapter entails the operational assumptions of the test case, the approach, and relevant findings.

A.1 Parameters

A.1.1 Timeseries:

- Yearly timeseries data for each run, with hourly datapoints.
- Both the uncertain timeseries data are based on historic datasets. This is done to make sure that the used timeseries are realistic. As said before, the goal of this test case is to be able to process the data correctly, provided that the data is correct/realistic.

A.1.2 Uncertain Demand Profiles:

- The demand profiles are based on historic data between 2005 and 2019. In region X1, the 3 households follow average national demand profiles, whereas the 3 households in region X2 follow an above average demand profile (1.1*average). Fractional electricity profiles have been taken from [19] and average annual consumption [kWh] from [18] (from [18], the S21 profile has been used (Electricity - Household with Night Consumption/Day Consumption ratio < 1.3 (or Grid User without an exclusive nightly rate if no consumption history))). The fractional data from [19] has datasets per 15 minutes, therefore the data has been transferred to average fraction per hour by taking the average of 4 values per hour. Then, for each year, the measured fractions are multiplied with the average consumption [kWh] of that year and with the number of households in that region (3). In [18], there is only demand data for 2009-2019. The demand for 2005-2008 has been interpolated from the 2009-2019 data. For region X2, those timeseries have been multiplied with 1.1 to create a "high demand" dataset. When looking at [18], there is a clear trend of decreasing electricity usage between 2010 and 2019, which is most likely due to the increasing energy efficiency of electrical components.

A.1.3 Uncertain Solar Profiles:

- Chosen: Solar timeseries from 2005 to 2019 are taken from [6]. They have been taken from a location in the Netherlands. Timeseries for solar panels inclined at 50 degrees (X1) and at 0 degrees are both used.

A.1.4 Supply Grid Power:

- Chosen: 0.2 kg CO_2/kWh from the grid expected in 2030 [2] [3] [4].
- Chosen: 0.2 kg CO_2/kWh from the grid expected in 2030 [2] [3] [4].
- Chosen: 0.125 EU / kg CO_2 –> CO_2 costs/kg [1].
- Chosen: 0.025 EU/kWh CO_2 tax (almost insignificant)
- Chosen: The grid connection is only available at location X3, to be able to model the effects of transmission losses.
- Assumed: Total price per kWh from grid = 0.5 EU/kWh.
- Assumed: Lifetime 50 years
- Assumed: Max capacity 25 kW (should be enough, can also be inf).
- Assumed: 15 EU/kW grid capacity is copied from the urban scale example.
- Assumed: Unlimited supply of electricity.

A.1.5 Batteries:

- Chosen: 55 EU per kWh storage capacity based on 2030 projections [7].
- Chosen: Round trip Energy efficiency of 90% (0,9487% single trip) [10].
- Chosen: Storage losses 5% per month [15].
- Chosen: Lifetime = 12 years in Pyreneen [16]?
- Chosen: Cyclic storage = true (SOC on timepoint 1 = SOC on last timepoint).
- Assumed: 4 kW of (dis)charge capacity per 1 kWh of storage capacity.
- Assumed: Initial State of Charge (SOC) of 50%.
- Assumed: Max total battery storage is taken as 150 kWh over total system.

A.1.6 Region X1:

- Chosen: 3 houses, house 1, 2, 3.
- Chosen: Inclination 50°
- Chosen: lat 51,75625 lon 4,16435
- Assumed: Total region available surface area for PV: 60 m2 [5].

A.1.7 Region X2:

- Chosen: 3 houses, house 4, 5, 6.
- Chosen: Inclination 0°
- Chosen: lat 51,75625 lon 4,16435
- Assumed: Total region available surface area for PV: 100 m2 [5].

A.1.8 Region X3:

- Chosen: Grid connection only.

A.1.9 Power Lines (underground):

- Chosen: Lifetime = 40 years [22]
- Chosen: Distance power lines:
  - X1 <-> X2: chosen as 0.6 km
  - X2 <-> X3: chosen as 2.5 km
  - X3 <-> X1: chosen as 1.5 km
- Assumed: Efficiency per km distance = 95%
- Assumed: Cost per distance = 0.01 (taken from urban scale example).

A.1.10 Cost

- Assumed: Interest rate chosen as 10%, taken from the urban scale example.

A.1.11 PV Panels

- PV1: Polycrystalline panel
  - Chosen: Efficiency = 18% [20]
  - Chosen: Resource per area cap = 5.84 m2 needed for 1 kWp of installed PV [20].
  - Chosen: Lifetime = 25 years [17]
  - Chosen: Expected O&M costs: 0.2 EU/kW/year [12].
  - Assumed: Parasitic efficiency 85% (invertors).
  - Assumed: Expected cost per 1 kWp = 700 EU/kWp.
  - Assumed: Export excess PV energy: 0.2 EU/kWh.
- PVtwo: Monocrystalline panels
  - Chosen: Resource per area cap = 4.99 m2 needed for 1 kWp of installed pv [21].
  - Chosen: Lifetime = 30 years [17].
  - Chosen: Expected O&M costs = 0.2 EU/kW/year [12].
  - Assumed: Parasitic efficiency 95% (inverters)
  - Assumed: Efficiency = 25%
  - Assumed: Expected cost per 1 kWp = 1000 EU/kWp.
  - Assumed: Export excess pv energy: 0.2 EU/kWh.

A.2 Uncertain Input Timeseries

A.3 Algorithm/Approach

After choosing the solar profiles, demand profiles and after defining the test case model, the first step “Inputs”, is completed. Then, the simulation settings in Calliope must be defined. For the objective function for this test case is chosen to minimize cost. For the SPOREs options, it was chosen to take 15% cost slack. Due to low computational power of 1 laptop (HPC connection was still

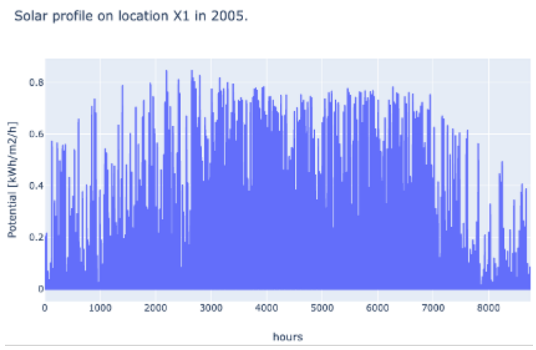

Figure A.1: An example of an annual (2005) time-series for the solar yield, used in case 1.

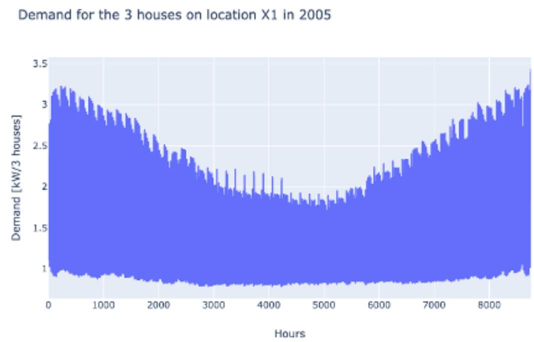

Figure A.2: An example of an annual (2005) time-series for the electrical demand, used in case 1.

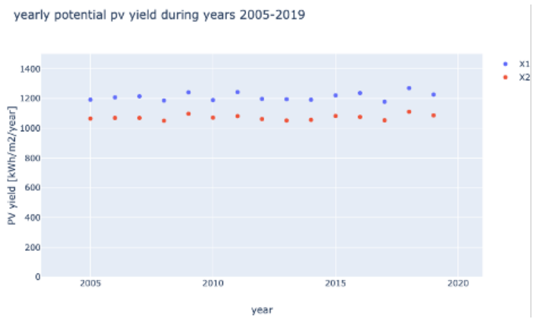

Figure A.3: Yearly averages for the solar yield in 2005-2019 for locations X1 (50°) and X2 (0°), used in case 1.

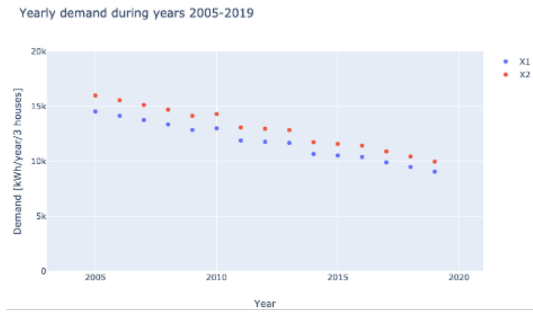

Figure A.4: Yearly averages for the electrical demand in 2005-2019 for locations X1 and X2, used in case 1.

in progress), it was chosen to run the test case with only 4 SPOREs. Meaning that for each MCA (Monte Carlo Analysis) scenario, the optimal solution, and 4 structurally different 15% more expensive solutions will be found. 15 MCA scenarios were chosen. Based on historic data (realistic data), with each scenario having a equal 1/15 (6,67% chance) probability of occurring. The following step is the stage 1 results, where the model behavior will be presented and where the possible capacity ranges for a cost slack of 15% will be discussed. Then configurations will be chosen based upon the configuration strategy. The chosen configurations' performance will then be tested on all the 15 possible Monte Carlo scenarios on the metrics Security of Supply, CO_2 emitted and total cost in the "operation" mode in Calliope. The results of this final step will lead to essential statements that can be found in the last chapter. The standard SPORE method is applied, only for case 2, the evolving average is used.

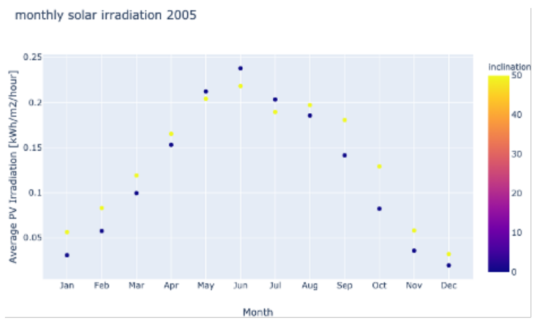

Figure A.5: Monthly averages for the solar yield in 2005 for locations X1 (50°) and X2 (0°), used in case 1.

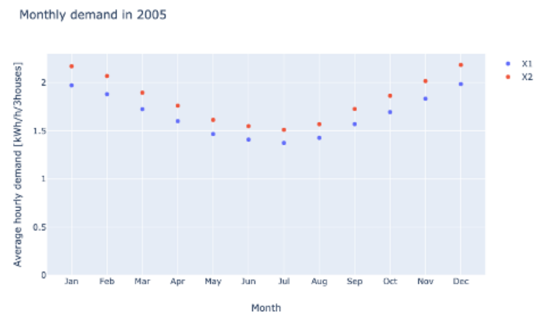

Figure A.6: Monthly averages for the electrical demand in 2005 for locations X1 and X2, used in case 1.

A.4 Solution Configuration Space

For all capacities except battery, the graph is in [kW], for the battery capacity, the graph is in [kW]. As explained in the last progress presentation, for each year, the optimal solution will be calculated (top left -> SPORE 0), and 4 SPOREs will be created, where the cost value is increased by 15%, but the solution space is changed. You can see that, within 15% cost slack, the model can also work without X1-X2 power cable connection, and that the PV/Pvtwo division can also change, while still being feasible.

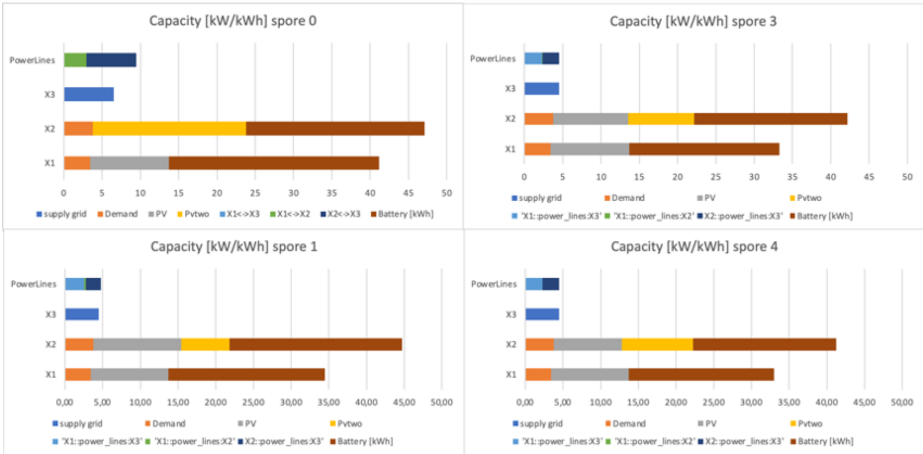

Figure A.7: Single solutions for SPOREs 0, 1, 3 and 4.

A.4.1 Normal Winter Week Behavior:

The model behaves as expected. All the PV power is directly used, and excess pv is stored in the batteries. When the batteries are empty, the grid power is used (figure A.8).

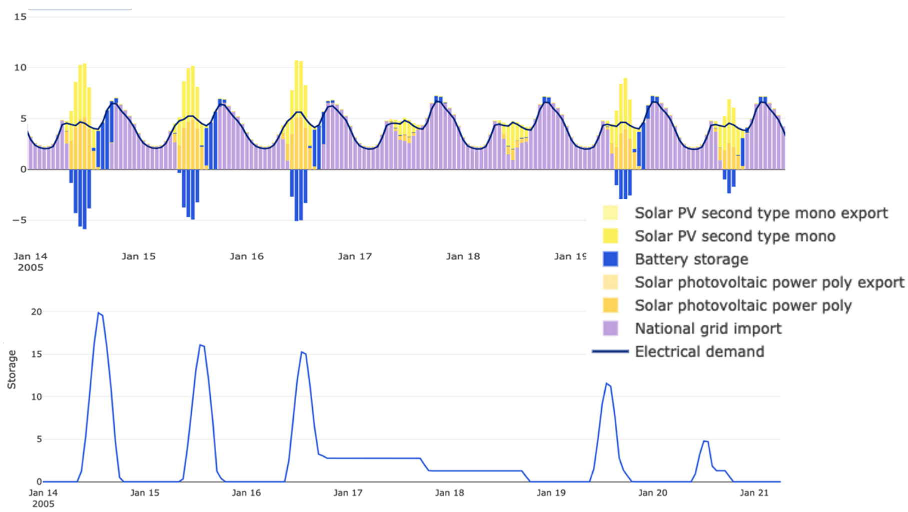

Figure A.8: Timeseries for the electrical and storage flows during a winter week, for input scenario 1, SPORE 0.

A.4.2 Summer Week Behavior:

Due to perfect foresight, the model always charges exactly what it will need the next day. Since there is a self-discharge loss modeled over time, the charging happens late on the day to prevent self-discharge losses. The remainder is sold back to the grid, since there is a positive export price.

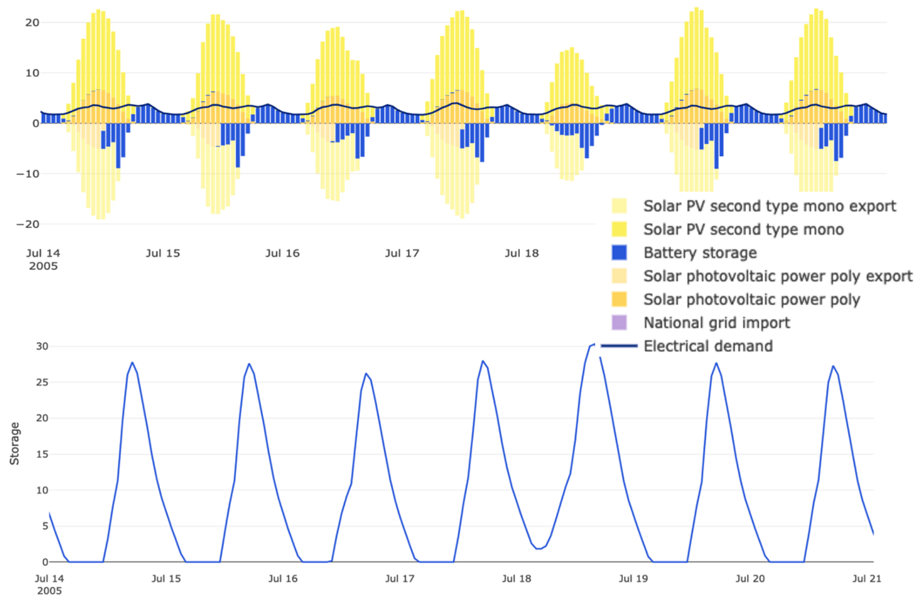

Figure A.9: Timeseries for the electrical and storage flows during a summer week, for input scenario 1, SPORE 0.

A.4.3 Storage Usage:

Despite being able to charge excess pv energy for the battery, the model prefers to sell the excess pv, and buy grid power later, since it is simply cheaper. Objective function = cheap as possible. Therefore, this happens. The 2 purple blocks of grid import cost less than storing instead of exporting.

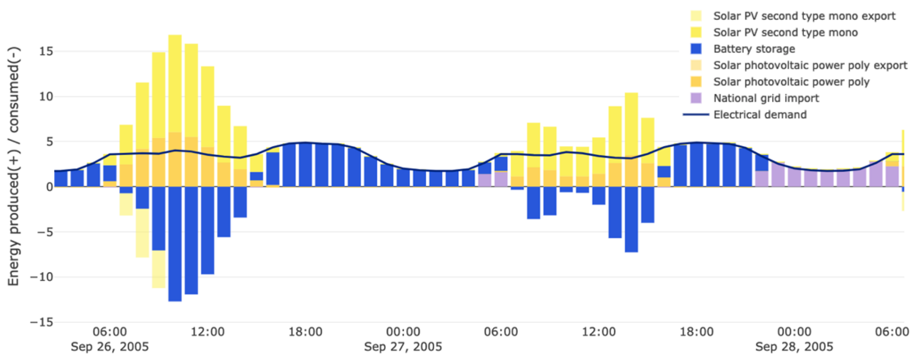

Figure A.10: Timeseries for the electrical flows during a week in autumn, for input scenario 1, SPORE 0.

A.4.4 Capacity Ranges:

The infomation of this subsection can be found in chapter 4.1.

A.4.5 Configuration Selection and Testable Configurations Continued:

The exact configuration dimensions can be found in table A.1. These dimensions have been used in Calliope to run the Evaluation against all 15 input scenarios.

Table A.1: The configurations, selected from the configuration solution space through the cumbersome selection method.

		Config 1	Config 2	Config 3	Config 4
Location	Technology	Capacity	Capacity	Capacity	Capacity
	Scenario	2008	2019	2015	2008
	Spore	optimal	optimal	spore 4	optimal
X1	battery	27.82 kWh (max)	19.201 kWh	15.196 kWh	20.932 kWh
X1	demand electricity	3.16 kW	2.1 kW	2.48 kW	2.21 kW
X1	pv	10.27 kWp (max)	10.27 kWp (max)	10.27 kWp (max)	10.27 kWp (max)
X1	pvtwo	0 kWp	0 kWp	0 kWp	0 kWp
X2	battery	23.37 kWh	17.584 kWh	16.736 kWh	17.942 kWh
X2	demand electricity	3.48 kW	2.31 kW	2.73 kW	2.43 kW
X2	pv	0 kWp	0 kWp	3.946 kWp	0 kWp
X2	pvtwo	20.04 kWp (max)	20.04 kWp (max)	15.42 kWp (max)	20.04 kWp (max)
X3	supply grid power	5.396 kW	3.171 kW	2.856 kW	3.519 kW
X1<->X2	Power lines	2.416 kW	1.577 kW	0.0216 kW	1.643 kW
X1<->X3	Power lines	0 kW	0 kW	1.454 kW	0 kW
X2<->X3	Power lines	5.396 kW	3.171 kW	1.402 kW	3.519 kW

A.5 Problems and Discussion Case 1

Small and general:

- Power lines had an unrealistic cost function,
  - Find and use an actual cost for cables
- A 10% interest rate is used for all components, but it's based upon nothing, Mikel said that this depends on the one investing:
  - Self-investing: interest rate should equal the inflation rate
  - Borrowing: interest rate should be equal to the lending rate
  - Investor: interest rate depends on the expected risk and on the interest rate if that money is spent on a different project.
- 4 SPOREs is not enough
  - HPC information received from Rene, we can use it to put the hpc to work.
- Can and should we include charging strategies in the model? (charge battery before selling to the grid)
- What should the SPORE slack % be based upon?
  - Samuel: design phase -> 50% uncertainty?
  - Francesco: use multiple slack %'s to see the effect.
- These solutions are of course based upon perfect representation of all components and uncertain variables, is that a problem?
  - Remember, within my scope is the method to work, not to be a fortune teller or to be a person that calls all the companies for what the exact component specifications are.
- The timeseries are still per hour, so the actual capacities should be capable to handle the peak demand.

Configurations choice:

- We are currently using only optimal or SPORE solutions as configurations, is that okay? Is it not also reasonable to use freestyle?
  - Using freestyle brings us back to including the human error into the equation.
- If a technology is still on the "essential technology" list, can the slack then be changed to remove it from that list?
  - Samuel: we will not do that, if they would have wanted that so badly, it could have been included in the model criteria (minimum/maximum capacity for that technology).

Operate mode:

- More metrics to score against, other than SOS, CO_2 & $
  - Yes (read back the tape)
- Storage is broken,
  - Will discuss this with Francesco
- For the results I used yearly costs, this should be returned to NPV
  - Yes, investigate economics behind the NPV a bit more.
- Is the 24-48 horizon window large and realistic enough?
  - We will see if it is a problem, if it is, we will investigate changing it, otherwise, we won't.

A.6 References Case 1

[1] [2] [3] [4] [5] [6] [7] [8] [9] [10] [11] [12] [15] [16] [17] [18] [19] [20] [21] [22]

B | Parametric Uncertainty Approaches Continued

B.1 Parametric Uncertainty: Stochastic Programming (SP)

Stochastic programming is based on solving a large equivalent of deterministic options that are defined by taking known stochastic variable distributions. It operates by making decisions before an uncertainty takes place, based on the information that the model has available at that moment. For example, for a solar and diesel-powered energy system, for each time stage, there is a known probability that solar energy production will be either high, medium, or low. However, deciding how much diesel fuel must be bought beforehand to cover the low solar production scenarios, without overspending, must be done in the most strategical way. The SP method calculates all possible scenario outcome probabilities (figure decision tree) and their consequences and finds the optimal hedging strategy that will result in the least amount of lost benefit (objective function) despite the actual scenario outcome.

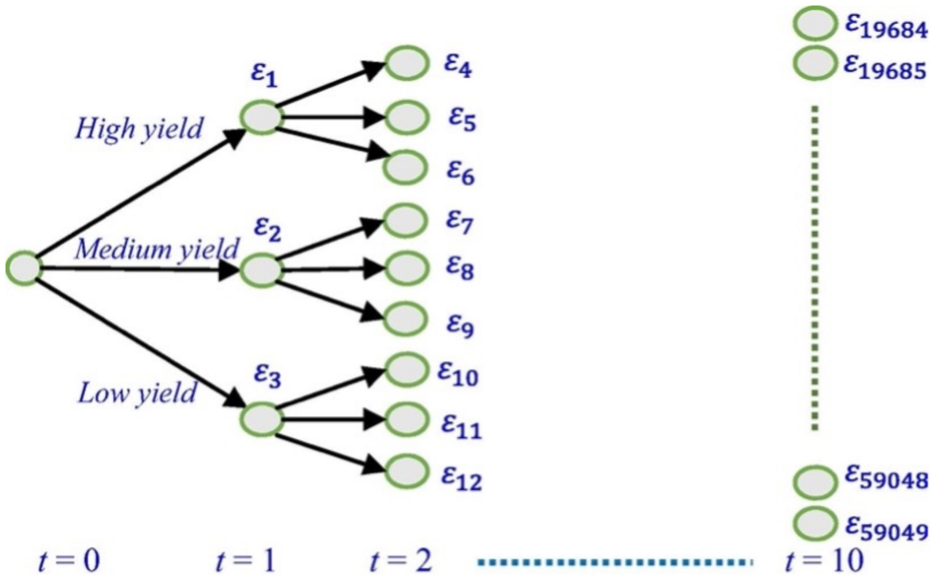

Figure B.1: Multiple stage, stochastic programming decision tree [2.2.2.0, Cobuloglu].

However, for every additional stage or additional uncertain parameter, the computational requirement for SP increases exponentially. It also requires a more in-depth information of the uncertain variables. Most studies have been limited to 2- or 3-time stages and no more than 10 possible "State of Worlds" (SOW), meaning possible results for uncertain variable (e.g., high, medium, low production for solar production). For long-term planning, the stage limit is though.

[2.2.2.0] Cobuloglu, H. I., & Esra Büyüktahtakın. (2017). A two-stage stochastic mixed-integer programming approach to the competition of biofuel and food production. Computers and Industrial Engineering, 107, 251–263.

[2.2.2.1] DeCarolis, J., Daly, H., Dodds, P., Keppo, I., Li, F., McDowall, W., Pye, S., Strachan, N., Trutnevyte, E., Usher, W., Winning, M., Yeh, S., & Zeyringer, M. (2017). Formalizing best practice for energy system optimization modelling. Applied Energy, 194, 184–198.

B.2 Parametric Uncertainty: Robust Optimization (RO)

Robust optimization is simply said, a type of worst-case analysis. It takes a simplified approach regarding addressing uncertainty. It defines a set of variables that can be uncertain and calculates optimal solutions while controlling the intensity of uncertainty of said variables through a "budget of uncertainty". If the budget of uncertainty is chosen as zero, all uncertain parameters reflect their nominal values. When the budget of uncertainty is maximized, the most pessimistic approach is taken by letting all uncertain parameters take extreme values, resulting in a highly robust solution. The robustness of the solution is therefore represented by the severity of the uncertainty budget [2.2.3.0, Ben-Tal].

Robust optimization can avoid a high computational burden and account for many uncertain variables by representing them in a simplified worst-case manner. In other studies, robust optimization was used for providing insights like the cost to hedge against uncertainty [2.2.3.1] and the identification of key hedging technologies [2.2.3.2, Labriet]. Despite being able to provide the most robust solution against maximum uncertainty, RO does not provide a strategy that can cope with all the possible outcomes [2.2.1.2,Yue]. Furthermore, RO is limited and only capable of addressing parametric uncertainty.

[2.2.3.0] Ben-Tal, A., El Ghaouni, L., & Nemirovski, A. (2009). Robust Optimization. Princeton University Press.

[2.2.3.1] Lorne, Daphne, & Tchung-Ming, Stephane (Oct 2012). The French biofuels mandates under cost uncertainty - an assessment based on robust optimization (INIS-FR–14-0518). France

[2.2.3.2] M. Labriet, C. Nicolas, S. Tchung-Ming, A. Kanudia, R. Loulou Energy Decisions in an Uncertain Climate and Technology Outlook: How Stochastic and Robust Methodologies Can Assist Policy-makers Informing Energy Clim. Policies Using Energy Syst. Model, Springer International Publishing (2015), pp. 69-91,

C Case 2 Continued

C.1 Parameters

Table C.1: Assumptions and Parameters of Case 2.

Technology:	Grid power	PV Poly	H2 pipe	Cables	Heat pipe	Cold pipe	Electrolyzer	Fuel cell	Hydrogen boiler
Technology type	supply	supply	transmission	transmission	transmission	transmission	conversion+	conversion+	conversion
Energy carrier in	-	-	hydrogen	electricity	heat	cooling	electricty	hydrogen	hydrogen
Energy carrier out 1	electricity	electricity	hydrogen	electricity	heat	cooling	hydrogen	heat	heat
Energy carrier out 2	-	-	-	-	-	-	heat	electricity	-
Lifetime [year]	50	25	25	25	25	25	14	14	10
Efficiency [%]	100	95 and 18	100	99.9%/km	99%/km	99%/km	77 and 19	55 and 40	100
Cost [EU/kW]	1000	1100 / kWp	15 EU/km	10 EU/km	10 EU/km	10 EU/km	1950	2500	2000
Cost [EU/kWh]	timeseries	-	-	-	-	-	-	-	-
Cost O&M [EU/year]	-	33	50 EU/km	-	50 EU/km	50 EU/km	-	-	-
CO2 [Kg/kW]	-	20	30 kg/km	1 kg/km	30 kg/km	30 kg/km	-	750	1
CO2 [Kg/kWh]	0.2	0.04	-	-	-	-	0.001102564	-	-
Storage CO2 [kg/kWh]	-	-	-	-	-	-	-	-	-
Storage cost [EU/kWh]	-	-	-	-	-	-	-	-	-
Interest rate [%]	0	0	0	0	0	0	0	0	0
Minimum SOC [%]	-	-	-	-	-	-	-	-	-
Self-discharge [%/hour]	-	-	-	-	-	-	-	-	-
kWh / kW ratio [-]	-	-	-	-	-	-	-	-	-
Storage initial SOC [%]	-	-	-	-	-	-	-	-	-
Min kW(h/p)	-	375 kWp	-	-	-	-	42 kW	42 kW	-
Max kW(h/p)	-	750 kWp	-	-	-	-	-	-	-
Resource	infinite	timeseries	-	-	-	-	-	-	-
Location	X1	X1	X2-X3-X4	X1-X2-X3-X5	X6X2X3X4X5	X2-X6-X5	X2	X3	X4

C.1.1 General

- Timeseries:
  - Yearly timeseries data for each run, with hourly datapoints (15 minute and 5-minute time-series have been translated to hourly datapoints, while keeping the maximum peak load the same).
- Chosen: global monetary interest rate of 3%.

Table C.2: Assumptions and Parameters of Case 2, Continued.

Technology:	Heat Pump	Cold storage	Heat storage	H2 storage	Battery	Electrical export	Heat demand	Cooling demand	Elec. Demand
Technology type	conversion	storage	storage	storage	storage	demand	demand	demand	demand
Energy carrier in	electricity	cooling	heat	hydrogen	electricity	-	-	-	-
Energy carrier out 1	cooling	cooling	heat	hydrogen	electricity	electricity	heat	cooling	electricity
Energy carrier out 2	-	-	-	-	-	-	-	-	-
Lifetime [year]	20	40	40	40	22	-	-	-	-
Efficiency [%]	900 (cop 9)	100 round trip	100 round trip	100 round trip	90 round trip	-	-	-	-
Cost [EU/kW]	1350	-	-	-	-	-	-	-	-
Cost [EU/kWh]	-	-	-	-	-	- 0.01	-	-	-
Cost O&M [EU/year]	6	-	-	-	10.91	-	-	-	-
CO2 [Kg/kW]	-	-	-	-	-	-	-	-	-
CO2 [Kg/kWh]	-	-	-	-	-	-	-	-	-
Storage CO2 [kg/kWh]	-	5	5	5	117.5	-	-	-	-
Storage cost [EU/kWh]	-	4	4	40	55	-	-	-	-
Interest rate [%]	0	0	0	0	0	-	-	-	-
Minimum SOC [%]	-	0.1	0.1	1	30	-	-	-	-
Self-discharge [%/hour]	-	0.005	0.005	0.00005	XXX??	-	-	-	-
kWh / kW ratio [-]	-	-	-	-	2.75	-	-	-	-
Storage initial SOC [%]	-	1	1	1	50	-	-	-	-
Min kW(h/p)	-	-	-	13000 kWh	-	-	-	-	-
Max kW(h/p)	-	730 kWh	2187.5 kWh	65000 kWh	-	10 kW	-	-	-
Resource	-	-	-	-	-	timeseries	timeseries	timeseries	timeseries
Location	X2	X6	X6	X3	X2	X1	X5	X5	X5

C.1.2 Chosen Physical Limitations for Neighbourhood of 100 Households

- PV: minimum is 375 kWp, maximum is 750 kWp (available rooftop area). Minimum is 50% as newly built houses are highly likely to have PV panels on them.
- Cold and Hot water storage: Physical Maximum of 125 m3 for 100 households for both types of storage. (2187.5 kWh hot storage, 730 kWh cold storage).
- Hydrogen storage: Minimum of 1 tube trailer, maximum of 5 tube trailers (safety issues).
- Electrolyzer = minimally 20% of average total demand per hour (avg demand = cool + heat + dhw + elec = 210 kWh/hour) -> 0,2 * 210 = 42 kW.
- Fuel cell = same as minimum electrolyzer -> 42 kW minimum capacity.
- Grid minimum installed capacity is 3450 kW

C.1.3 Uncertain Profiles

- "Uncertain" demand profiles, 100 households are used, consisting of 10 rows of 10 houses, resulting in 80 terrace households, and 20 side/corner houses. Each house is assumed to have an average surface area of 100 m2 and 2 floors [invulversie].
  - Heating demand
    * The total heat demand [kWh] consists of both the domestic hot water demand (DHW) and the Thermostat heating demand (TH). The base case is 100%, the high demand case is 120%, and the frugal case is 80%.
      · DHW profile from 2017 is used from [secret W+B file], and multiplied with 100 households annual demand from [invulversie]
      · TH profile is calculated through [secret W+B file], based on historic temperature timeseries from 2017, measured in "de Bilt". And multiplied with 100 households annual demand from [invulversie].

    * The total heat demand is assumed to use the 65 C hot water, over a Delta Temperature of 15 C. (Tout heating demand = 50C)

  – Cooling demand:

    * The cooling demand is calculated in a similar manner through [secret W&B file] as the heating TH demand, but it is flipped and multiplied with the annual cooling demand for these houses from [invulversie].

    * The base case is 100%, the high demand case is 120%, and the frugal case is 80%.

    * The total cooling demand is assumed to use the 15 C cold water over a Delta Temperature of 5 C (Tout cooling = 20C).

  – Electrical demand:

    * The electrical demand fractional profiles from [Nedu] 2017 are used and multiplied with the total annual demand of the 100 households. For this case, S21 profiles are chosen [hy.60].

    * The base case is 100

- "Uncertain" solar profiles:

  – Chosen: Solar timeseries are based upon 2017 historic data, measured in "de Bilt". The timeseries are in kWh produced per installed kWp [kWh/kWp/hour] and taken from [6].

- "Uncertain" grid electricity price profiles

  – Chosen: price timeseries, based upon the historic data from 2017, from [hy.70], [hy.71].

C.1.4 Heat Pumps

Water source Heat pump: for small domestic projects it costs around 2000 EU/kW of installed capacity, for larger domestic/commercial projects, the capex are 1150 EU/kW (calculated from pounds) [hy.1]. Another source mentions a capital cost of (2009 pound = 1.26 2021 pound –> 1350 EU/kW installed) 1350 Eu/kW [hy.2] [hy.3]. 1350 EU/kW is chosen. For a commercial/public water heat pump system, a typical lifetime is 20 years[hy.2] [hy.3]. Another source mentions a heat pump lifetime of 15 years [hy.7]. 20 years is chosen. The operational costs of such a system is (one 2009 pound = 1.26 pound in 2021 –> 6 Eu/kW/year.) 6 Eu/kW/year [hy.2] [hy.3]. The COP for heating water depends on the difference of the "ambient temperature" (the input water/air) and the targeted heating water temperature. COP = $0.0023 * (Toutout - Tsourcein)^2$ – $0.2851 * (Toutout - Tsourcein)$ + 10.677 –> for a Toutout of 65 C, the COP with 20 C input would be 2.505, rounding up to 2.5 for the model. For an output temperature of 15 degrees for the floor heating cooling, the COP would be around 9. [hy.11].

C.1.5 Heat and Cold Storage

Heat and cold storage (sensible water tank heat storage) is modeled with a round trip efficiency of 100%, but a self-discharge of 0.5% per hour assuming highly insulated storage vessels. Cost of it ranges between 0.1-10$/kWh storage capacity [hy.4], 4 EU/kWh is chosen. Hot water storage should be done at 60 degrees Celsius to kill bacteria, 65 degrees is chosen [hy.5]. The cold-water storage will occur at a temperature of 15 C, as the only cooling demand is the floor heating, which occurs around 15C [hy.45] [hy.9]. The floor heating (DHW) is done at 35 degrees [hy.10]. For the thermal energy system, there is always unlimited water available at a temperature of 20C (ambient temperature). This is used to justify the assumptions on water quality for heating and cooling purposes. CO_2 at production is neglected. The lifetime is estimated at 50 years.

C.1.6 Electrical Li-ion Battery

Nissan leaf battery leasing in the Netherlands is offered at 100 EU / month –> 1200 EU / year / 40 kWh = 30 EU / year / kWh. The power of one Nissan leaf battery = 110 kW [hy.6]. Resulting in a 2.75 charge cap / storage cap ratio. Chosen initial and minimum state of charge of the batteries is 30% [hy.46]. Lithium-ion batteries produce between 39 and 196 kg CO_2 / kWh of charging capacity, take average of 117.5 kg CO_2/kWh is used [hy.8]. lifetime is 22 years [hy.47]. Leaseplan promises minimum capacity and efficiency etc. roundtrip efficiency lithium-ion batteries = 90% . Self-discharge for lithium-ion batteries it is 2.5 percent per month [hy.48].

C.1.7 PEM Fuel Cell

PEM fuel cells are chosen. Fuel cell CHP electrical and thermal efficiency if used in chp form, electrical = 40%, thermal = 55%. [hy.19]. When looking at the lifetime of a PEM fuel cell, the CO_2 emissions, emitted during production, 750 kG CO_2 / kW. [hy.19]. Fuel cell costs in 2020 are 2500 EU/kW installed [hy.15]. PEM electrolyzer lifetime: 40000 hours, but with an ESTIMATED uptime of 33%, 13,6892539357 years of lifetime is expected. Rounded up to 14 years. This 33% is based on an expectation that excess energy is available mostly during the day in the summer [hy.18]. Fuel cell PEM operating temperature 50-100 degrees. [hy.28] [hy.17], 80C is chosen.

C.1.8 PEM Electrolyzer

PEM electrolyzer is chosen. The CAPEX of a PEM electrolyzer are 1950 Euro/kW for PEM systems. The OPEX are assumed negligible since they mostly depend on the electricity "price" [hy.21]. Electrolyzer CO_2 emissions (from electrolyzer production) are 0,043 kg CO_2 per kg of h2 (39 kWh = 1 kg h2), resulting in 0,001102564103 kg CO_2 per kWh of h2 produced for the electrolyzer [hy.22]. PEM electrolyzer electrical efficiency is between 65-82% [hy.13], 80% is chosen. The cooling water will be between 80 and 90 degrees [hy.25] [hy.26]. 80 C is chosen. Operation costs are negligible, as they are mostly dominated by the electricity price [hy.21]. Lifetime is expected at 40000 hours. With 33% expected uptime since mostly active during hot summer days, 14 years of lifetime is expected [hy.18]. For every kWh of electricity, 80% will go into h2 production, and 90% of 20% will go into heat recovery [hy.20]. To include the hydrogen storage compression energy cost, an average value of 2 kWh per kg of h2 stored is used [hy.24]. This is included in the total efficiency of the electrolyzer (77% electrical efficiency, 19% heat efficiency, rest is used for compression).

C.1.9 Hydrogen Storage

Hydrogen storage CO_2 emissions (from storage tank and compressor production) 0,004358974359 kg CO_2 per kWh of hydrogen compressed and stored in the storage tank [hy.22]. Hydrogen compression is expected to be around 2 kWh per kg h2 produced and is included in the electrolyzer efficiency. It is based on 3-5 compression stages, to an outlet pressure of 445-495 bara. The range comprises both regularly air-cooled systems, as well as actively cooled system [hy.24]. This compression electrical requirement is implemented within the efficiency of the electrolyzer, meaning that next to the electrolyzer efficiency of 75%, the additional requirement of 2 kWh per kg h2 produced is included as well [hy.24]. CSD (compression, storage, and decompression) in 2020 is 0,68 EU/kg h2 –> 0,01743589744 EU/kWh h2. [hy.23]. For the specifications of hydrogen storage, tube trailers are used. One tube trailer has a volume of about 16.2 m3 [hy.61]. If hydrogen is stored at 300 bar (commonly done), the density is 20,537 [hy.62], 334.2 kg can be stored in 1 tube trailer. Since 1 kg of hydrogen has a potential of 39 kWh, 13000 kWh can be stored in 1 tube trailer. 10 EU/kWh storage capacity is assumed. A storage loss of 2.4% per month xis assumed.

C.1.10 Hydrogen Boiler

Hydrogen boiler burns around 300 degrees [hy.29]. has 100% efficiency. Costs are taken as the equivalent cost of normal gas boilers [hy.50] and will be around. Average boiler for 1 household is 30 kW, average cost for 1 boiler is 1750 EU, cost per kW is 60 EU [hy.51], [hy.52], rounded up to 100 EU/kW. CO_2 due to production is neglected.

C.1.11 PV

PV Polycrystalline panels with 18% efficiency [20]. Lifetime of 25 years [17]. O&m costs of 33 EU/kWp/year [hy.32]. 0.04 kg CO_2 / kWh produced by solar panels [hy.33]. installation cost of 1100 EU/kWp [hy.32]. system efficiency of 95%. Minimum installed capacity 375 kWp (50% of average rooftop surface), maximum installed capacity 750 kWp (100% of average rooftop surface). Since these are newly built households, the regulations dictate that they are built as sustainably as possible, resulting in at least 50% coverage of pv panels for the rooftops. Average rooftop area per household is 55 m2 [hy.63], let's say that 80% of that area is effectively usable, for 100 households, this results in 4400 m2 available for pv panels. 6 m2 is required to install 1 kWp of the chosen pv [20], resulting in a max pv capacity of 750 kWp. The average angle for the households is taken as 45 degrees in the Netherlands [hy.64]. It is assumed that the households are built with their roofs aimed towards the south.

C.1.12 Electricity Export

Max 10 kW of export available, with 0.01 EU/kWh profit. This is chosen to impede dumping excess pv energy on the grid when the sun shines, but to create the possibility to return energy to the grid. The capacity costs of export are 0 EU/kW, as the excess electricity can flow through the supply grid technology.

C.1.13 Grid

In 2030, it is expected that the applied carbon tax will be equal to 0.150 EU/kg of CO_2 emitted [1]. It is also expected that in the Netherlands, the grid will consist for 0.2 kg CO_2 emissions per kWh of produced electricity [2], [3], [4], as the expected share of renewable generation will increase. To calculate the costs for new grid connection, per single household, a 3phase 3x50A connection is considered, resulting in 1611 EU / 3x50A connection, which is 34500 W (230*50*3) connection. This will be by default the minimum installed capacity since each household will be equipped with it. Meaning that per kW, the cost for grid connection is equal to 33,6695652174 EU/kW [hy.111] [hy.112] [hy.113]. For 100 households, this means that the minimum installed capacity is 3450 kW. This is chosen as fixed to cope with the electricity peak demands that are missed due to the hourly electrical demand resolution. The assumed lifetime of such a grid connection is estimated at 50 years. It is also assumed that an infinite amount of electricity can be taken from the grid. O&M costs are neglected for the grid connection as they will most likely be paid for by the consumer.

C.1.14 Electrical Cables

50 years of lifetime is considered [hy.117]. 10 EU / m OR (supersimple case) 100 EU /kW. We assume a 1% loss per km. 10 kg of CO_2 per m per kW assumed.

C.1.15 Heating Pipes

50 yeas of lifetime is considered [hy.115]. 200 EU / m [hy.116] OR (supersimple case) 100 EU /kW. We assume a 1% loss per km. 10 kg of CO_2 per m per kW assumed.

C.1.16 Cooling Pipes

50 yeas of lifetime is considered [hy.115]. 200 EU / m [hy.116] OR (supersimple case) 100 EU /kW. We assume a 1% loss per km. 10 kg of CO_2 per m per kW assumed. . For all transmission technologies, it is assumed that, as they will only portray a small part of the costs, that the peak demands can be supplied by the storages and pipes themselves.

C.1.17 Hydrogen Pipes

50 years lifetime is considered [hy.115]. 500000 EU per km. OR (supersimple case) 100 EU /kW [hy.114]. 10 kg of CO_2 per m per kW assumed. . No leaking is assumed.

C.2 Simulation Options

Table C.3: Simulation parameters for case 2.

General:	
Temporal resolution:	hourly
Temporal range:	year
Calliope version:	0.6.6.post1
Mode:	spore
Spore options:	50, 15%, evolving average
Solver:	Gurobi
Solver io:	Python
Ensure feasibility:	True
BigM:	10 e 9
Cyclic storage:	True
Zero threshold:	10 e -10
Objective cost:	monetary 1, spores 0.

C.3 Additional Results

Pictures of the cost and CO_2 distribution of the components.

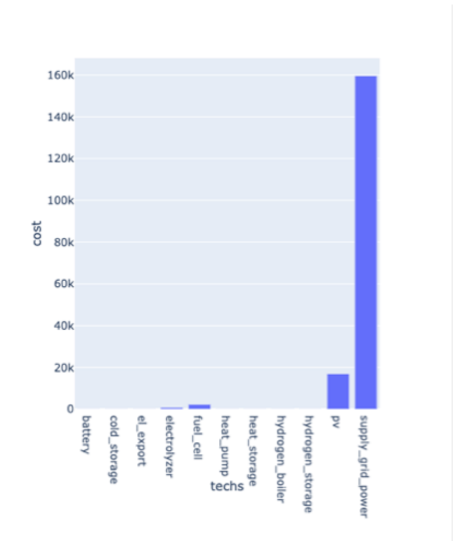

Figure C.1: CO_2 distribution SPORE 0 scenario 1.

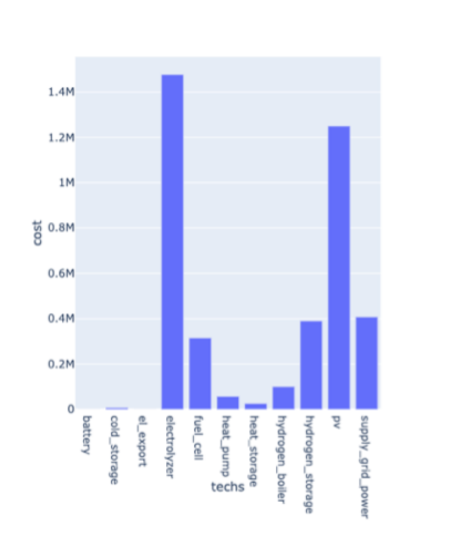

Figure C.2: Cost distribution SPORE 0 scenario 1.

C.4 Overview

C.5 References Appendix Case 2

[hy.1] [hy.2] [hy.3] [hy.4] [hy.5] [hy.6] [hy.7] [hy.8] [hy.9] [hy.10] [hy.11] [hy.13] [hy.15] [hy.17] [hy.18] [hy.19] [hy.20] [hy.21] [hy.22] [hy.23] [hy.24] [hy.25] [hy.26] [hy.28] [hy.29] [hy.32] [hy.33] [hy.45] [hy.46] [hy.47] [hy.48] [hy.50] [hy.51] [hy.52] [hy.60] [hy.61] [hy.62] [hy.63] [hy.64] [hy.70] [hy.71] [hy.99] [secret W+B file] [invulversie] [nedu] [hy.111] [hy.112] [hy.113] [hy.114] [hy.115] [hy.116] [hy.117] [6] [17] [20] [1] [2] [3] [4]