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Does the Electricity Sector in 2050 Belong to Solar Power?

A Case Study on Portugal

Master's thesis in Sustainable Energy Systems

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Department of Space, Earth and Environment
CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2020

Master's thesis 2020

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Master's Thesis 2020
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Typeset in LaTeX
Printed by Chalmers Reproservice
Gothenburg, Sweden 2020

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Abstract

Southern European countries, such as Portugal, can successfully use solar power to meet their climate targets given their favorable exposure to insolation. Solar power is a variable renewable energy source (VRES). Consequently, other electricity generation sources and energy storage technologies become important to work in harmony with solar power to ensure a resilient electricity system.

This thesis considers the year 2050 and Portugal as basis of its assumptions. Further, it uses a green-field investment model to outline which uncertainties are associated with solar becoming the major source of energy in the electricity sector in 2050. Additionally, it investigates how solar power being the major electricity supplier in the electricity sector influences the system Levelized Cost of Electricity (LCOE). An extensive sensitivity analysis, by performing a Monte Carlo analysis, evaluates different uncertainties correlated with different technologies' development: investment and fuel costs. Also different scenarios are studied to better understand how different uncertainties impact the optimal share of solar power. These scenarios include expensive battery storage, carbon capture and storage (CCS) technologies, and an addition of hydrogen demand.

The results show that solar power, despite of being primarily influenced by the solar power investment cost, is also impacted by the investment cost of battery storage. When battery storage investment costs is, on average, lower than 91 €/KWh, solar power becomes the major electricity generation source of the electricity sector when the solar power investment cost is lower than 650 k€/MW. Still, at times when the demand cannot be met by only solar power and the excess energy stored in batteries, wind power, CCS technologies, and biogas power plants become important. Nuclear power becomes extremely important at times when solar power is frequently complemented. The system LCOE, from decreasing the solar power investment cost from 800 k€/MW to 200 k€/MW is reduced by 24%, reaching a lowest of 48 €/MWh. CCS technologies promote an increase in system LCOE by 4 €/MWh, while adding a demand for hydrogen lowers system LCOE by 2 €/MWh.

Keywords: Carbon Capture and Storage (CCS), Expensive Battery Storage, Hydrogen Demand, Monte Carlo Analysis, System Levelized Cost of Electricity (LCOE).

Acknowledgements

I would like to express my genuine gratitude to my supervisors, Viktor Walter and Professor Carlos Silva, and to my examiner Lisa Göransson: Viktor Walter, 'tack så mycket' for all the time you spent with me and with my numerous questions. It was a pleasure to having you by my side; Professor Carlos Silva, 'muito obrigada' for the opportunity that you gave me which allowed me to enjoy as much as I did when writing my master's thesis in Chalmers; Lisa Göransson, 'tack så mycket', for allowing me to work in such an interesting project, which, undoubtedly, showed me how eager I am to deepen my knowledge in the transition to a carbon-neutral society and thus make that as my next future challenge.

Also, I would like to extend my gratitude to Carlos Canelada, that more than being my opponent, became a friend.

I am also extremely grateful to the division of Energy Technology. Thanks for allowing me to meet such intelligent, positive, welcoming, and friendly people.

Christian Azar, 'muito obrigada' for provoking curiosity in me to explore the energy transition field by both your course, Sustainable Energy Future, that I had the pleasure to attend, and your encouragement to write my master's thesis in this field.

Becky Bergman and Linnéa Johansson, thank you very much for all of the time that you put into my master's thesis, with your excellent feedback.

To all of my friends and family a big 'obrigada': To my mother and Tomás, for being the best part of me; To Vera, Chico, and Helder for being them; To Bordes, my eternal pride, and to Pim, who I always will miss.

Last but not least, to my best friend, Erik.

Maria de Oliveira Loureiro, Gothenburg, July 2020

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Abbreviations

ATB Annual Technology Baseline.

BloombergNEF Bloomberg New Energy Finance.

CO_2 Carbon Dioxide.

DEA Danish Energy Agency.

DSM Demand-Side Management.

EV Electrical Vehicles.

FLH Full-Load Hours.

GAMS General Algebraic Modeling System.

GHG Greenhouse Gas.

IPCC Intergovernmental Panel on Climate Change.

IRENA International Renewable Energy Agency.

LCOE Levelized Cost of Electricity.

LP Linear Programming.

NREL National Renewable Energy Laboratory.

RNC 2050 2050 Carbon Neutrality Roadmap.

Solar PV Solar Photovoltaic.

UNFCCC United Nations Framework Convention on Climate Change.

VMSs Variation Management Strategies.

VRESs Variable Renewable Energy Sources.

1

Introduction

Ever since the mid-20th century, an acceleration in global warming has been observed, caused by the increase in global atmospheric carbon dioxide (CO_2). This acceleration has made renewable energy production, such as solar and wind power, gain significant importance due to the characteristics they share as carbon-neutral power sources [1]. Solar and wind power are also referred to as intermittent electricity sources because the power output cannot be controlled, due to their dependence on weather and geographical conditions [2]. Nevertheless, it is necessary to maintain the load balance, that the generation output (supply) equals the load (demand), at all times. Due to this, an increased share of variable energy renewable sources (VRESs) in the electricity sector can be a challenge during the times when renewable production is low [3].

Since the output of the VRESs fluctuates at the same time that the load balance needs to be fulfilled, both solar and wind power should be used in connection with a more dispatchable source of energy to ensure that the power supply equates the demand. Consequently, the strategies and technologies that manage the mismatch in supply and demand are important for an electricity system composed of high shares of VRESs.

Southern European countries, such as Portugal, can use solar power to meet their climate target given their favorable exposure to insolation [4]. However, as a renewable source, solar power has an inherent challenge to meet the demand for electricity during hours of low production. For this reason, variation management strategies (VMSs), such as other electricity generation sources, flexible demand, and storage, become important to ensure a resilient electricity system with electricity generation meeting the demand. There are already several studies that emphasize the importance of the synergy between solar power and battery storage [5]–[9]. Nevertheless, it is still not clear, as a consequence of a wide range of different parameters used in the aforementioned studies and hence no coherency, how varying generation mixes and costs parameters influence the cost-efficiency of solar photovoltaic (Solar PV) technologies.

In conclusion, there is a need of studying how different generation mixes of the electricity sector and technologies' cost influence the cost-efficiency of solar power.

1.1 Aim & Scope

The overall aim of this master's thesis is to outline which uncertainties (development of technologies) are associated with solar becoming the major source of energy in the electricity sector in 2050 and how these uncertainties influence the system Levelized Cost of Electricity (LCOE)[1]. This master's study investigates the interaction between different technologies associated with an increase in solar share. It looks at the effect of the development of different technologies, such as investment and fuel cost of different technologies, that combined with solar power, aim to prevent possible bottlenecks[2]. This study considers technologies such as wind power, storage technologies, conventional fossil fuels, biofuels, nuclear plants, and thermal power plants with Carbon Capture and Storage (CCS) technologies. These technologies may either promote or prevent the cost-efficiency of solar power in the market as an alternative to dispatchable electricity generation source. This thesis also outlines the impact of an increase in hydrogen (H_2) demand on the industry sector.

The goal of this study is to evaluate how different uncertainties impact the optimal share of solar power in the electricity sector. Therefore, the following questions will be answered with the study:

- Under which conditions will solar power become the major electricity generation source of the electricity sector?
  - How is the cost-competitiveness of solar power influenced by the investment and fuel cost of other technologies composing the electricity sector?
    - How is the system LCOE impacted by different uncertainties?
  - Which technologies become important to ensure the load balance, that cannot be fulfilled solely with the use of solar power?
  - How important will wind power be in the new electricity sector? Will wind power be a complement to solar power? Or can it be seen as a barrier to the development of solar power?

1.2 Method & Delimitations

A linear investment and dispatch model was used in this study to optimize both the total system cost and dispatch generation. The regional model, eNODE, was firstly presented by Göransson *et al.* [10]. As a green-field investment model, it is applicable for systems where high shares of renewables are under consideration. eNODE does not take any capacity currently in place into consideration but instead invests in a new electricity generation system. This is a linear programming (LP) model, which means that all the non-linear relations will be linearized. This LP model

[1]System LCOE is the same as average electricity cost.
[2]Bottlenecks define a supply-chain situation, which is characterized the supply being limited by the system capacity.

only uses real-world geographical areas to get correlations between the electricity demand, heat demand, and VRESs' production curves. Additionally, eNODE accounts for a widespread variability, due to the inclusion of start-up costs and time, the minimum load level of thermal generation and charging losses from storage. The cost-minimizing model runs with a three-hour time resolution while taking different constraints into consideration, e.g., fulfilling the hourly electricity demand and constraints both in terms of CO_2 emissions and weather resources. Furthermore, this model has also been used in other studies, papers, and theses [10]–[13].

This study uses both pre-existing data in the model and additional data required for this thesis - technologies' investment and fuel costs. The financial data added in the model is a combination of projections suggested from different databases [8], [12], [14]–[22]. All the parameters are set in ranges of lower and upper limits to better carry out an extensive sensitivity analysis using Monte Carlo analysis and thus, better evaluate the different uncertainties that might be associated with the adoption of solar power in the electricity system. This thesis takes the year of 2050 and Portugal as the basis of its assumptions, in terms of electricity demand, CO_2 and resource weather constraints, and both technical and financial properties of the technologies which compose the electricity sector.

1.3 Outline of the Thesis

This report is divided into seven chapters:

- **Chapter 1 - Introduction:** This chapter introduces the topic of this thesis, the increase of solar share in electricity sector, using Portugal as a case study;
- **Chapter 2 - Background:** This chapter provides a brief overview of different types of thermal power plants, VMSs, technologies' learning curves, and energy system modeling;
- **Chapter 3 - Literature Review**: This chapter contains general information regarding climate change and the increased usage of VRESs over the last years. Also, relevant studies are synthesized and a gap in the current scientific literature is presented;
- **Chapter 4 - Methodology & Input Data:** This chapter defines the model used in this work and introduces the input data which is used in the Monte Carlo analysis. Lastly, it presents the model scenarios along with their characteristics, which are used in this thesis to more accurately answer the questions addressed in section 1.1;
- **Chapter 5 - Results:** This chapter shows the obtained results;
- **Chapter 6 - Discussion & Future Work:** This chapter discusses the findings and compares them with the previous studies already done. Also, this chapter suggests further studies that can be done to extend or deepen the scope of this thesis;

- **Chapter 7 - Conclusion:** This final chapter concludes the thesis.

2

Background

This chapter is dedicated to giving the essential background to better understand the method, results, and discussion of this master's thesis. In particular, this chapter provides a brief overview of different concepts such as the types of load power plants, variation management strategies, learning curve and life cycle of technologies, and energy system modeling.

2.1 Type of Thermal Power Plants

The conventional electricity system has been until recently composed of dispatchable power plants. These generation power sources account for technologies such as coal-fired power plants, nuclear power plants, hydropower with dams, and gas-fired power plants. Dispatchable electricity generation technologies ensure the load balance between demand and supply at all times.

Additionally, these technologies can be grouped into three categories, according to their operating strategy: base, intermediate, and peak-load power plants. The categorization can be seen in Figure 2.1, which shows the operation of the different types of load power plants in the left graph: the baseload power plants fulfill the minimal load by constantly operating throughout the year; the intermediate-load power plants address the variation of load throughout the day; the peak-load power plants operate when the demand reaches exceptional peaks. The right graph results from sorting the curve in the left graph, in descending order. Baseload power plants account for more than half of the total annual electricity consumption. Moreover, the other part of the load varies over a range of time, between intermediate and peak-load power plants. The peak-load power plants only operate for a few hours of the year.

Baseload power plants are characterized by having high investment costs and significantly low running costs. Consequently, these plants run at a constant output, which makes it unjustified, from a financial and technical perspective, to either change the output level or to shut down and startup according to the demand. Baseload power plants include nuclear power and coal power.

Intermediate-load power plants, which are also known as mid-load or load-following power plants, run for extended periods at a time but generally with low full-load hours (FLH)[1]. These plants can be shut down more easily than the baseload power plants if required, e.g., during periods with low demand, which makes them a better fit for electricity demand fluctuations. Natural gas fire plants and hydropower plants are considered as intermediate-load power plants.

Lastly, peak-load power plants are used to manage and meet the peaks in demand. Consequently, they run for a limited duration annually and can be shut down easily when the demand requires. This type of plant includes diesel or fuel-oil power plants.

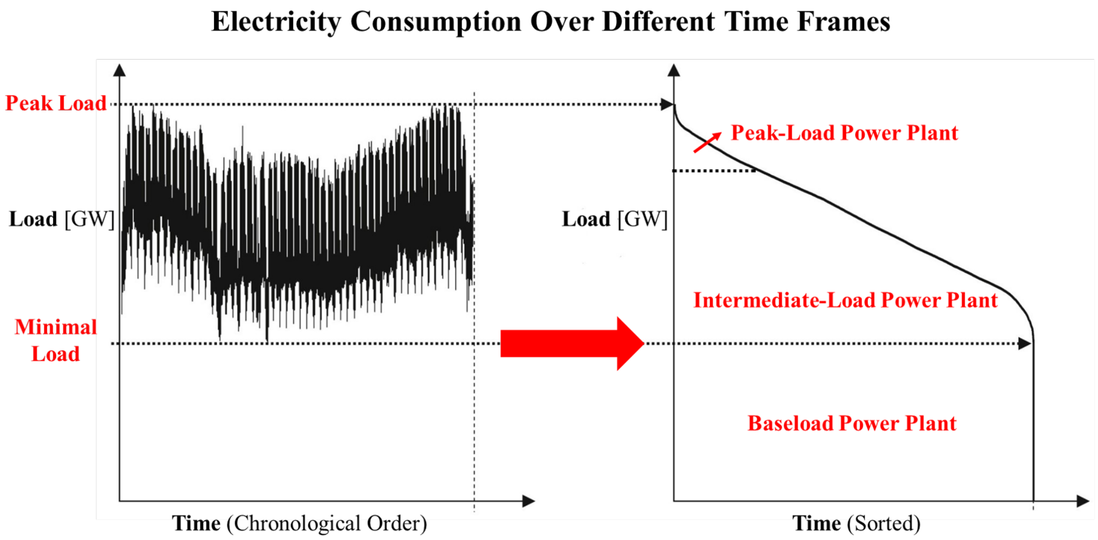

Figure 2.1: Energy demand varying over one year. Adapted from the original [23].

As Schlachtberger *et al.* [24] explain, the type of thermal power plants existent in the electricity sector are in a great part dependent on the amount of VRESs share. At a high share of VRESs (above 50%), there is very little room for baseload power plants, while intermediate-load power plant usage increases significantly at a VRESs share above 40%. Finally, when it comes to peak-load power plants, these plants become extremely important for VRESs share higher than 50%, reaching its maximum at a VRESs share of 70%.

The current electricity sectors still account for a significant part of baseload power plants, such as coal and nuclear power. At times when VRESs production is relatively low, the baseload power plants are extremely important to assure the load balance. Nevertheless, due to the constant output of these dispatchable power plants, the total power generated can exceed the demand when favorable conditions for solar and wind power realize. Consequently, and to avoid excessive curtailment[2] of VRESs, dispatchable power plants need to adapt their output to the current demand of the system, by providing ramping capabilities and have a larger range of operation [25]. This leads to efficiency penalties in thermal power plants, which can

[1] FLH= $\frac{ElectricityGenerated}{CapacityInstalled}$ [h]

[2] Surplus of power output may have to be dumped or the power plant output turned down or switched off for a while.

result in lower financial efficiency and an increase of emissions from these power plants[3] [26].

2.1.1 Thermal Power Plants

An electricity sector with a high share of VRESs, due to the inherent intermittency of these sources, is characterized by its major demand for flexible resources. Therefore, thermal power plants can bring the desired flexibility to the system at times with low renewable energy production. Hence this thesis looks at the fuel cost of three different types of thermal power plants in an electricity sector accounting for solar power generation. This thesis includes nuclear power plants, conventional fossil fuels associated with CCS technologies, and biofueled power plants.

Nuclear power plants generate heat, which produces steam, by splitting uranium atoms, in a fission process. As fuel is not burnt, they do not produce greenhouse gas (GHG) emissions. Nuclear power plants are characterized as baseload power plants. Notice that although there are no nuclear power plants in Portugal, nuclear power is imported both from Spain (which have five power plants) and France (where nuclear power accounts for the largest electricity generation share).

CCS technologies, which are typically intermediate-load power plants, are capable of separating, transporting, and permanently storing CO_2 underground to avoid it to enter the atmosphere. CCS technologies can help the decarbonization of the electricity system, even by using fossil fuels [27]. In order to explore the uncertainty of this technology in a future low-carbon electricity system, two types of thermal power plants with CCS technologies are modeled: bio-coal CCS[4] and bio-natural gas CCS[5], operating in a closed cycle turbine.

Biofuels originate from renewable sources derived mainly from plants, microorganisms, animals, and waste. This master's study looks at the effect of using this kind of electricity generation source in a future carbon-neutral electricity sector. Three different types of biofueled power plants are used: biomass power plants and biogas power plants, both in closed and open-cycle turbines. Biofueled power plants are often characterized as baseload (pure biomass) and peak-load (biogas) power plants.

2.2 Variation Management Strategies

Electricity systems composed of a high share of VRESs must find solutions that can control their intermittent production, without compromising the cost efficiency of the whole system. These solutions are known as variation management strategies (VMSs).

[3] It refers to emissions per KWh, considering that total emissions are expected to go down.

[4] Bio-coal CCS is a combination of hard coal and biomass associated with CCS technologies. It is composed of 90% coal and 10% of biomass.

[5] Bio-natural gas CCS is a combination of natural gas and biogas with CCS technologies. It is composed of 88% natural gas and 12% biogas.

VMSs are all the solutions that can control the unbalance between demand and generation, which might be caused by extensive use of VRESs. The range of different types of VMSs is relatively diverse. To facilitate the comprehension of the different VMSs, Göransson and Johnsson [19] introduce a new way of categorizing them in three types of VMSs: *shifting, absorbing*, and *complementing* strategies.

Shifting strategies, such batteries, are useful to store the excess energy for later use, for times when the generation profile itself cannot meet the demand and thus guarantee the load balance. As shifting storage technologies are typically expensive and limited in time to charge and of storage, these technologies are more favorable for short-duration variations between excess and deficit of energy generated. Thus, shifting storage technologies better suit the generation profile of solar power than wind power.

Absorbing strategies, like electric boilers, have the power of transforming excess energy into other energy carriers. These strategies are useful for more durable curtailment or low net load periods[6] for increasing the value of VRESs.

Lastly, *complementing* strategies, as their name suggests, complement the fluctuation of VRESs production. These kinds of strategies support the periods with low VRESs share. It accounts for both flexible generation and electricity consumers that shut down their generation during high net load times. Dispatchable power plants are considered *complementing* strategies [7].

Additionally, Johansson and Göransson [12] outline how different types of VMSs have different impacts on the system cost and introduce two new terms highly relevant to the use of VMSs: *system-limited* and *resource-limited*. *System-limited* technology describes a technology that, for high levels of adoption in the system, is the major factor for decreasing the marginal value of additional energy generation from VRESs, and by doing so, discourages further investments. On the other side, *resource-limited* technology refers to a technology that, due to its low share in the system when compared with other technologies, is outcompeted, and thus does not affect the marginal value of the system as a whole.

Some VMSs[8] have been included in this thesis, in order to investigate how they can affect a system with a high share of solar power.

2.2.1 Energy Storage Technologies

Energy storage technologies provide flexibility to the system, which facilitates the adoption of VRESs. These technologies can utilize the fluctuation in price during peak and non-peak hours, due to their storage capability [29], promoting the shifting

[6]Net load is characterized by the total load minus expected electricity generation from VRESs [28].

[7]Baseload power plants act as *absorbing* strategies. Due to their high investment cost, they produce electricity at all times except during low net load events.

[8]Important to note that the electricity generated from thermal power plants is also considered VMSs.

of energy from times with excess of energy to times where the demand is higher than the supply.

Therefore, this work considers two types of energy storage in order to analyze the potential effects on the whole sector: battery storage and H_2 storage. Battery storage is considered a *shifting* strategy since it has a high cost of storing per unit of energy stored. H_2 storage, with relatively low cost of storing per unit of energy stored, is either considered *absorbing* strategy or *complementing* strategy since electrolyzers produce H_2, which later can be converted into electricity, for the most part of the year. In this thesis, H_2 is defined as a fixed demand, thus is characterized as *complementing* strategy.

2.2.2 Curtailment & Special Case of Wind

Solar power as a non-dispatchable electricity generation source has times where its supply exceeds the demand but also times when the vice-versa applies. As such, this master's thesis also includes two strategies that may be used to deal with solar power's intermittence.

There are times when it is impossible to accommodate all the VRESs generation while ensuring the efficiency of the electricity system. Thus, the possibility for VRESs curtailment can prevent further investment in both grid and storage extension by limiting the power output of VRESs power plants some hours in a year [30].

Wind power, although it is also a VRES as solar, can play an interesting role in future electricity sectors, where the power generation mainly originates from solar power. This likely happens in locations where there is a synergy between solar and wind resources, like Portugal. As Portugal is characterized by extensive coastal area, wind is often stronger in the evening and night due to the temperature gradients between the ocean surface and land surface. Consequently, when solar power generation is insufficient, like evenings and nights, wind power can complement solar power, by offering an extra power generation to meet the demand. However, this synergy vanishes when both solar PV and wind power are produced at the same time and are relatively cheap. Consequently, these two VRESs can guarantee the major electricity generation share and hence start to compete.

2.3 Technology's Learning Curve & Life Cycle

Learning curves, also known as experience curves, are explained by Grübler [31] as reflecting how the technological development of a specific technology impacts the economy of that technology. The author describes learning curves as an exponential model characterized by the decrease of the unit cost of production at a decreasing rate as experience is gained. The gathered experience of a specific technology, despite time, is strongly correlated to its production volume. Figure 2.2 shows a learning curve.

Additionally, McDonald and Schrattenholzer [32] explain that, from the interpretation of learning curves, it is possible to estimate the learning rate. The learning rate measures the pace of technology development, e.g. a learning rate of $x\%$ means that a cost of a given technology drops by $x\%$ when a technology's cumulative installed capacity is doubled.

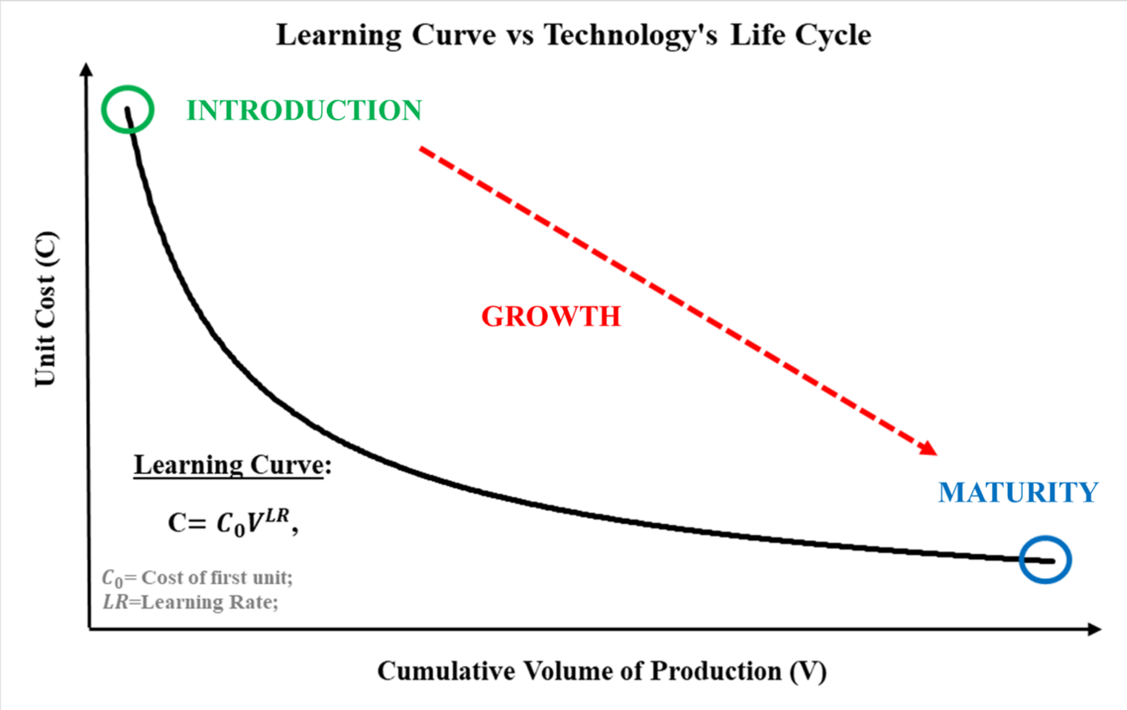

Figure 2.2: Technology's learning curve and life cycle.

In Figure 2.2, it is possible to see how a technology's learning curve is associated with its life cycle. As Shahmarichatghieh *et al.* [33] clarify, technology development is associated with three different phases: *introduction*, *growth*, and *maturity*. The *introduction* phase is associated with a niche market of new technology. In this phase, the applicability of the new technology is low and thus there is a high risk of investment. The consumers barely know the potential of the new technology, and for that reason, the demand is limited. Due to this, the introduction of new technology is mostly expensive, due to the reduced integration in the market. The cost tends to decrease as the technology moves from concept into an application, which is associated with demand growth. As the demand for new technology grows, the technology passes to the second phase, *growth*, which is characterized by an increase in the technology's application. The risk of investment decreases as the technology is integrated into a supply chain. In this phase, as the competition significantly increases, a feedback loop between the cost of the technology and the development of technology is created. To successfully respond to the competition of other technologies, the technology cost is reduced. The reduction in cost causes, and is caused, by an improvement of the technology and thus greater adoption in the market. Finally, in the *maturity* phase, the risk of investment in a specific technology is low and the demand is almost constant. Due to the technology development, which offer more efficient services, and the cost reduction, which is a consequence of optimization in the supply chain, the technology accounts for a high share in the market.

Rubin *et al.* [34] emphasize that learning curves reflect the evolution of different energy sources. Experience curves show a feedback loop between the reduction of costs and the cumulative installed capacity of a specific energy supply technology. Hence these curves are important to understand the technology development, which is beneficial to explain the evolution of energy systems and the implication on addressing energy-related issues, such as climate change.

Figure 2.3 illustrates the learning curve of both VRESs between the years 2010 to 2018. IRENA [35] suggests a solar power's learning rate of 34%. At the same time, it also indicates that wind power has a learning rate of 20%. Moreover, Figure 2.3 highlights that wind power is already a maturated technology since 2010, while solar experienced the growth phase until approximately 2017. Nowadays, solar power is already assumed as a maturated electricity generation source.

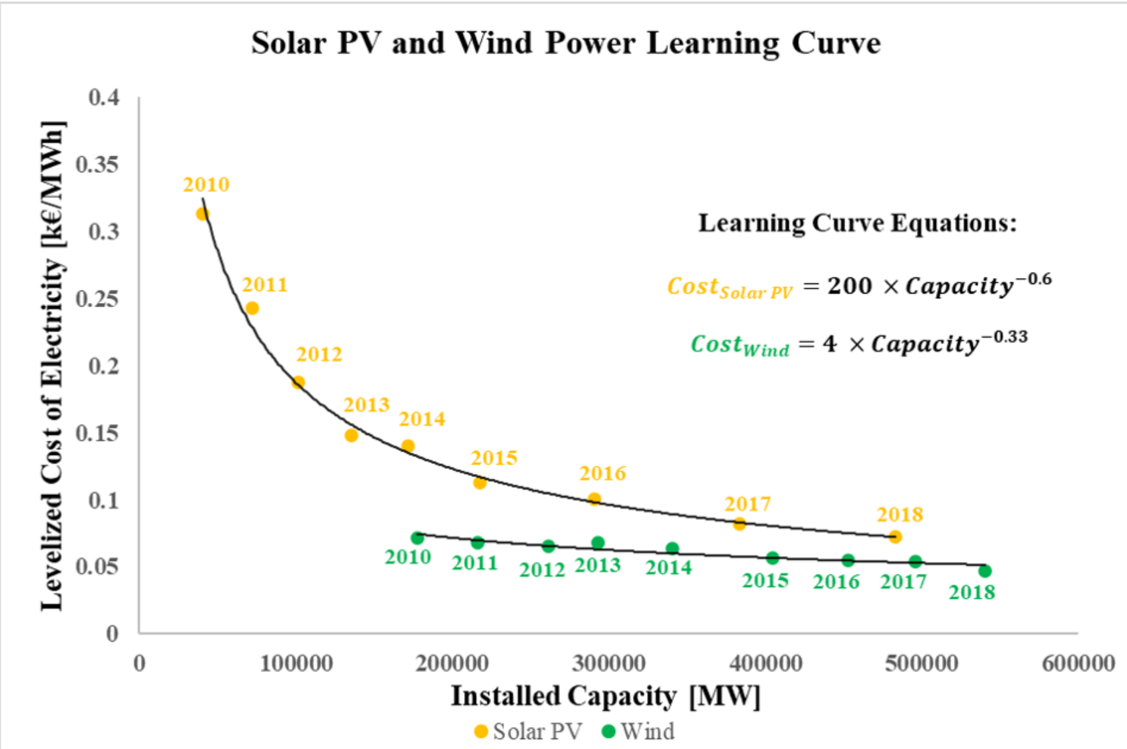

Figure 2.3: VRESs' learning curve over time - 2010 to 2018. Empirical data obtained from IRENA [35], converted from dollar to euro (with 2018's average conversion rate of 1.18).

2.4 Energy Systems Modeling

According to Bhattacharyya and Timilsina [36], models have been used to analyze energy systems since the early 1970s. Ever since then, modeling energy systems have had different policy-making motivations: "better energy supply system design given a level of demand forecast, better understanding of the present and future demand-supply interactions, energy and environment interactions, energy-economy interactions, and energy system planning". Thus, there is a wide variety of energy system models with different scopes and approaches.

To differentiate the different energy system approaches, McFarland *et al.* [37] suggests that there are two modeling system categories: *top-down* and *bottom-up*. *Top-down* modeling prioritizes the economic interactions, rather than the technological, and thus represents each sector of the economy by an aggregation of functions, i.e., bridges the gap between economy and capital, labor, and natural resources. In contrast, *bottom-up* provides great technological details, focusing on how to ensure the load balance from a technical perspective for an exogenous demand. The technologies' activity is often defined by linear correlation and based on engineering data of both life-cycle costs and thermodynamic efficiencies.

Furthermore, it is also important to separate the two different terms - *simulation* and *optimization* - when it comes to energy modeling systems. As Lund *et al.* [38] defines, *simulation* represents a system by reproducing and envisage the performance of that very system under a real context set of conditions. *Optimization* provides optimal system design, by using a set of well-defined energy system design characteristics, known as decision-variables, which are computed to either maximize or minimize an objective function subject to constraints.

The model used in this master's thesis uses a bottom-up approach. Additionally, the model used in this thesis is a linear programming optimization model, that obtains both the objective function and the constraints as linear functions of the decision variables. Furthermore, the model used in this master's study will be described in detail in chapter 4.

3

Literature Review

This chapter describes how literature addresses climate change by increasing the market for VRESs. Also, relevant studies are synthesized and a gap in the current scientific literature is presented.

3.1 Global Warming: Paris Agreement & Carbon Neutrality 2050

The United Nations Framework Convention on Climate Change (UNFCCC) adopted the Paris Agreement in December 2015. By signing the agreement, the involved parties committed to a common climate target. The main goal of the Paris Agreement is to keep "the increase in the global average temperature to well below 2°C above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5°C above pre-industrial levels" [39].

The Intergovernmental Panel on Climate Change (IPCC) emphasizes the importance of the difference of this half a degree on the effect of global warming. The IPCC suggests that the impacts of a global temperature increase of 1.5°C will be severe, but still much preferable to what an increase of 2°C would render. The emissions pathways for achieving these two temperatures goals are undoubtedly different [40]. The IPCC Special Report "Global Warming 1.5°C" concludes that reducing the CO_2 emission by 80% to 90% to pre-industrial levels by 2050 is sufficient for limiting the increasing global temperature to 1.5°C. However, it is still insufficient for reversing the unsustainable global change caused by climate change. Consequently, IPCC highlights the huge need for net-zero carbon emissions by 2050 and thus achieving climate neutrality to counter the otherwise irreversible path ahead [41]. Climate neutrality implies a net-zero global carbon footprint and given the current society's oil-dependency, shifting towards low carbon energy sources, like VRESs, is essential. Transitioning to a carbon-neutral society becomes increasingly financial and technologically possible, as the cost and technology of solar and wind power advances and can compete with traditional technologies [42].

Different countries create their own roadmaps on how to reach neutrality by 2050 and Portugal is no exception. In 2016, in accordance with the Paris Agreement, the Portuguese government targeted carbon neutrality by the end of 2050, enforced by the decarbonization of the national economy. The 2050 Carbon Neutrality Roadmap (RNC 2050) describes how all societal sectors can, and must, contribute to meet the goal. Moreover, the report emphasizes the responsibility of the electricity and the transport sector as the two major contributors to Portugal's CO_2 emissions. The statistical data shows that the aforementioned sectors were responsible for 50% of the total emissions between 2007-2017. Therefore, the RNC 2050 supports the reduction of carbon intensity in the electricity produced in Portugal by relying on renewable sources of energy for electricity generation. The RNC 2050 outlines the importance of both VRESs and energy storage technologies to the expected increased demand for electricity in the future Portuguese society, which is expected to be characterized by a 100% carbon neutrality [43].

3.2 Variable Renewable Energy Sources & Load Balance

As aforementioned, there is an urge for decarbonizing the global economy and hence achieving carbon neutrality by 2050 the latest. The use of VRESs is the major strategy to mitigate climate change [44]. The term variable is important as it excludes controllable renewable energy sources, such as biomass, geothermal power, and hydropower. Consequently, both solar and wind power are the considered VRESs in this work.

Even though both solar and wind power are variable energy sources, their fluctuations differ in terms of how to predict them. Solar power's availability varies according to insolation, which depends on factors such as the current timeframe (day-night) and meteorology conditions. Furthermore, solar power generation does vary seasonally, yet the greatest difference can be observed daily [45]. Wind fluctuations are also hard to predict in a long-term perspective because, as Hedegaard and Meibom [46] puts it, they are dependent on numerous factors, such as different timescales for instances intra-hour, intra-day, weekly, and seasonally. As a result of solar's and wind's intermittent nature, an electricity sector composed of a high share of VRESs does not easily safeguard the load balance required for an electricity system's reliability. VRESs' shortcomings can, however, be addressed using VMSs. VMSs are technologies that manage the mismatch in supply and demand, owing to their controllable and predictable characteristics. VMSs are extensively discussed in section 2.2

3.2.1 Solar Photovoltaic Systems & Battery Storage

The market of renewable energy, especially the market for solar power, has grown rapidly over the two last decades. Stern [47] explains the reason why solar PV system cost has fallen by nearly 80% in the last ten years. The main reason for the cost decline is the fact that the installed renewable capacity has seen a sharp increase, as a consequence of the solar PV cells being composed of silica (silicon dioxide). These conclusions adhere to the data extracted from the International

Renewable Energy Agency (IRENA) [35], depicted in Figure 3.1. The data suggest a steep increase in the global installed capacity from 2000 until 2019, from 0.8 GW to 580 GW. At the same time, the investment cost decreased by approximately 74% from 2010 until 2018 where it cost about 1000 €/kW.

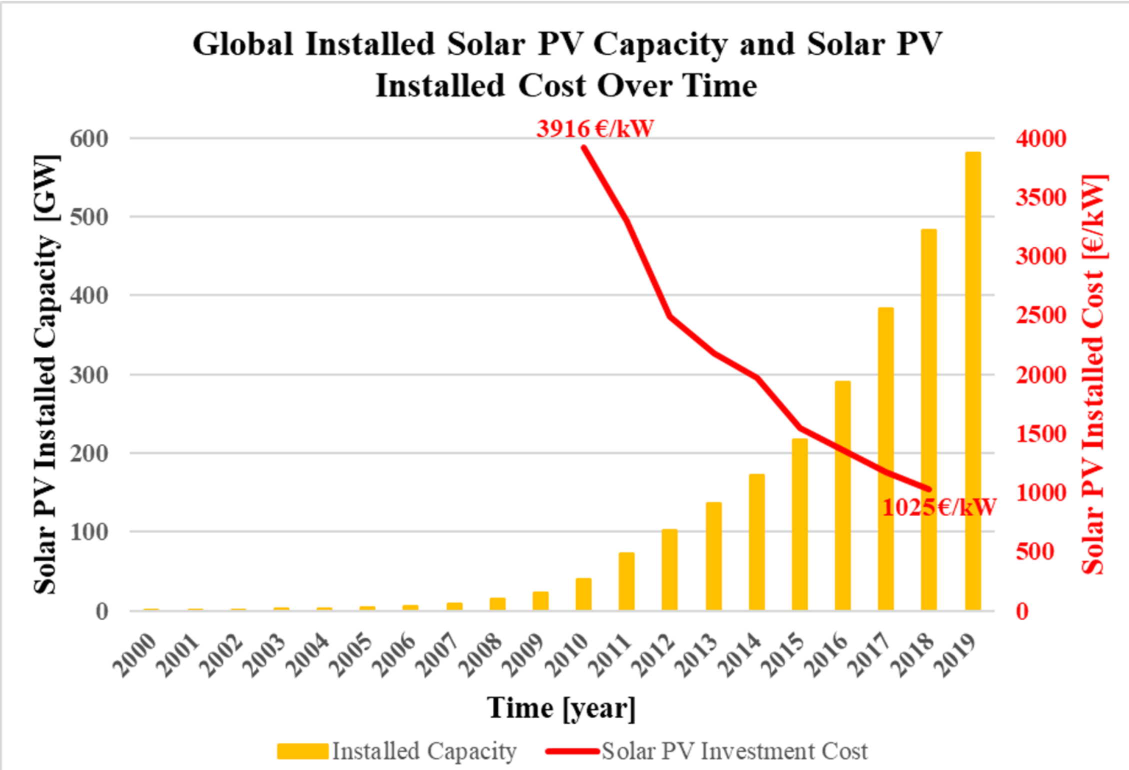

Figure 3.1: Global installed solar PV capacity and solar installed cost over time. Empirical data obtained from IRENA [35], converted from dollar to euro (with 2018's average conversion rate of 1.18).

While the solar power market is increasing, the world energy demand is expected to keep on rising. As can be observed in Figure 3.2, energy consumption has increased by 56% from 1990 until 2018.

To ensure that the increasing energy demand will not be met with conventional energy sources, such as coal and gas, governments have incentivized the adoption of renewable technology, including solar power. Through these incentives, continuous technological innovation is facilitated, which increases solar's power cost-efficiency. The continuous improvements in solar power results in solar power's promising potential to meet the energy demands of the future, at minimal environmental impact and at a reduced cost [48].

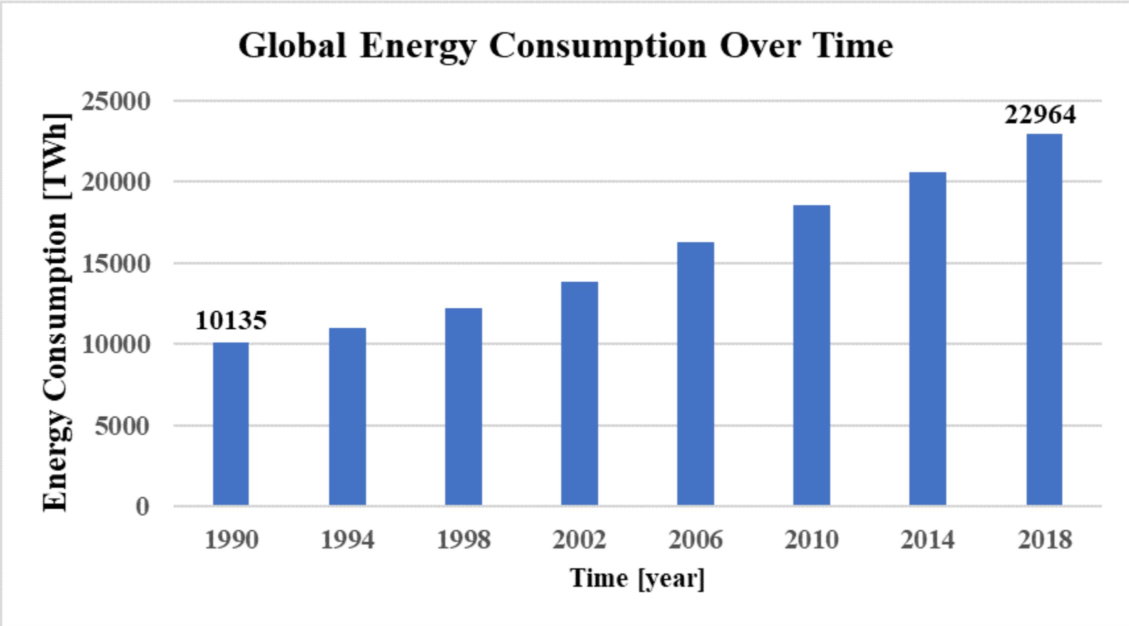

Figure 3.2: Global energy consumption over time. The data is retrieved from [49].

As the renewable share does increase, the electricity sector requires extra flexibility. The flexibility can be addressed by storing the energy produced by solar over hours, days, weeks, or months [50]. Since batteries store the excess of the energy produced and then deliver it at times of electricity deficit, these energy storage technologies can decrease the short-time demand and supply discrepancies [51]. The reduction of the cost of battery storage, which is caused by the increase of electrical vehicles (EV), is accurately accompanying the sharp drop in solar power cost [52].

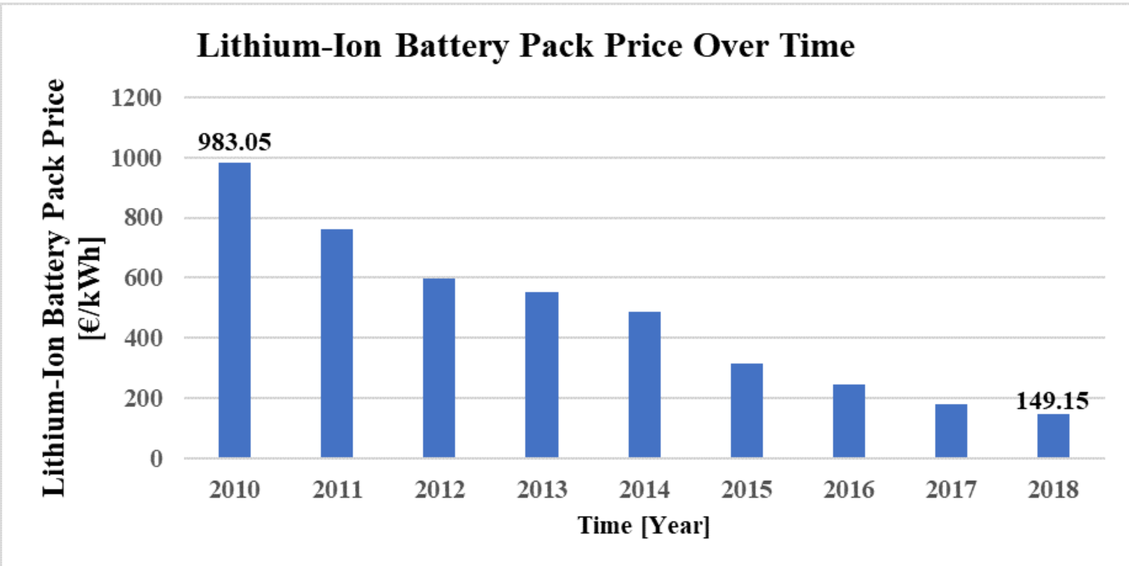

Figure 3.3: Lithium-ion battery pack price over time. Originally from BloombergNEF) [53], converted from dollar to euro (with 2018's average conversion rate of 1.18).

This conclusion is in consonance with the data provided by Bloomberg New Energy Finance (BloombergNEF) [53], illustrated in Figure 3.3. The figure conveys a major drop in battery storage pack price (about 85%) since 2010, reaching an average price of 149.15 €/kWh in 2018. The driving force for the declining price of batteries lies in the research and development from industry and in the mass production for batteries [54]. Due to the batteries' storage nature and the drop of their cost in the last years, batteries hold immense possibilities to make solar power able to transform the power systems into 100% carbon-neutral.

3.3 Previous Studies

Several studies have been focusing on the importance of the use and the increase of VRESs. Most of the studies look particularly at how solar PV systems, combined with energy storage technologies, can promote the transition of the electricity sector to 100% carbon-neutral. Many papers already investigate how to address the same issue, namely climate change, such as [5]–[9]. Even though the authors base their research on the importance of solar share, they do not address the research questions described in section 1.1 that this thesis sets out to do. The studies [6]–[9], use a green-field cost optimization model, contrary to [5], which uses a simulation model.

Frew *et al.* [5] simulate an electricity sector in 2050 composed of a high share of solar PV. The authors use a dispatch model to link capacity expansion and production cost to study the feasibility of the simulated electricity system. Due to the rapid decline in both solar PV systems and energy technologies storage costs, the authors suggest that in 2050, 55% of the total generation of the electricity sector in USA could be accounted for by solar power, which is based on one of the scenarios proposed by Cole *et al.* [55]. In that case, the electricity system would efficiently replace a huge part of the hours of dispatch power generation by storage, and at extremely sunny hours curtailment would become the best solution to maintain the load balance and the system frequency. Consequently, the increase in solar capacity in the electricity system leads to a drastic decrease in the energy price and even hours with zero price (which are strongly correlated with curtailment hours).

Victoria *et al.* [6] explore the impact of energy storage technologies on achieving the CO_2 emission targets and sector-coupling scenarios. This study proposes that different types of energy storage technologies are better suitable for certain situations, i.e., electrical batteries are preferable for an electricity sector composed of a high solar share. In this very example, the reason is the need for short-term storage, while H_2 storage is better suited for smooth power fluctuations, such as electricity typically generated by wind.

Schlachtberger *et al.* [7] vary the solar power and battery storage cost separately and evaluate the impact that this has on the total system cost. This research paper suggests that with the decrease in solar power cost, the capacity installed, the energy generated, and the curtailment for wind power decreases. Also, the system cost decreases linearly with both lower solar PV systems and battery storage costs. This linearity is identified by the authors for solar power cost greater than 300 k€/MW and battery storage cost greater than 232.5 k€/MWh. For costs below the previous values, the decline in total system cost is even steeper.

Atsmon and Ek Fälth [8] explore the changes in system LCOE by varying both solar PV systems and battery storage costs. The authors found that decreasing the cost for solar power by 50% and battery storage by 62%, reduces the system cost by about 27% to 34%, depending on the geographical area, which results in a lower system LCOE.

Villar *et al.* [9] emphasize, by using a techno-economic performance analysis, the importance of solar power self-consumption. The authors suggest that to encourage the self-consumption for solar power, it is important to combine solar PV production and other technologies. These technologies, such as energy storage technologies and demand-side management (DSM)[1], are considered to be a solution to the mismatch of demand profiles and PV generation. Also, this study reveals that the existence of these synergies would promote the increase of the overall efficiency, by reducing the costs associated with distributed energy grid integration.

No research was found that both explores the effects on electricity system cost, by the increase of solar share either in Portugal or Mediterranean regions (e.g. Spain and Italy), and looks at solar power from a utility-perspective, which is what this thesis sets out to investigate.

According to the aforementioned papers, due to the wide range of parameters where no consensus is found, it is not clear at which extent varying generation mixes and cost parameters influence the cost-efficiency of solar power and thus the system LCOE. Additionally, none of the previous research studies model CCS technologies or explores the industry sector for an addition H_2 demand, which is investigated in this master's thesis. Further, in chapter 6, there is a comparison between the findings of this thesis and the aforementioned previous studies.

[1]Shift of consumer demand for electricity, by encouraging the consumer to use less electricity during peak hours, or to move the time of electricity use to off-peak times.

4

Methodology & Input Data

This chapter presents the model used in this study and introduces the input data used for the Monte Carlo analysis. The input data consist of both pre-existing data, which was already implemented in the model, but also financial data which was added to the model - investment and fuel costs. Lastly, it presents the model scenarios along with their characteristic conditions which are used in this thesis.

4.1 Model

The regional model, eNODE, which applies the General Algebraic Modeling System (GAMS)[1] was firstly presented by Göransson *et al.* [10]. This bottom-up regional model defines the electricity sector as a single region. Thus, eNODE does not consider the possibility of inter-regional transmission of electricity. The model only uses real-world data for each of the different geographic locations. Hence different correlations for each location are used in the modeling such as energy and heat demand but also different real-world context restrictions, such as VRESs production curves and area limitations for investmenting in VRESs. As a green-field investment model, eNODE is applicable for electricity systems where high shares of renewables are under consideration. This means that it does not consider any pre-established capacity but instead invests in a new optimal mix of technologies [10]. The model accounts for a wide set of technologies and thus a more precise and realistic electricity system is modeled. Each technology is characterized by proprieties such as investment, running[2], and cycling[3] costs.

Additionally, eNODE, which uses LP to minimize the total system cost, meets the electricity demand while respecting different constraints in terms of CO_2 emissions and weather resources. The LP-model was run with a three-hour resolution for a full year, which represents the year 2050 in terms of electricity demand, technologies costs and assumptions on CO_2 emissions. In this very thesis, the cap of carbon emissions was set as zero. The Monte Carlo analysis was run several times and for different scenarios, which consumed a lot of time. Owing to this, the three-hour resolution was adopted to improve the run-time of the model, which is significantly

[1] GAMS is a high-level modeling software suitable for mathematical optimization.
[2] Running costs include fuel costs and operation and maintenance costs.
[3] Cycling costs are both start-up and part-load costs.

higher for an hourly resolution. The difference between results from different time resolutions is imperceptible, partly due to the use of cheap battery storage technologies that easily smoothen fluctuations on such a short time scale.

4.1.1 Model Formulation

As aforementioned, this thesis used eNODE, a model that was previously developed within *The Department of Space, Earth and Environment – The Division of Energy Technology*. Thus, the green-field investment model formulation used in this master's is thoroughly described by Johansson and Göransson [12].

Even though the model used was not developed exclusively to address the research question that this thesis proposes to do, it is important to understand how the model ran from a more general perspective. For that reason, the model accounts for a range of sets (upper-case), parameter (italic upper-case), and variables (italic lower-case) (appendix A.2).

The objective function of the model is to minimize the total system cost (c_{tot} [€/year]) for one year (T). The total system cost includes investment cost (C_{inv} [€/kW]) with respective investment (i [kW]) and annuity factor (A), as a function of lifetime and discount rate, fixed operation and maintenance cost (OM_f [€/kW]), running (C_{run} [€/MWh]), and cycling cost (C_{cycl} [€]) of each electricity generation technology (P)[4] which composes the electricity system. The total system cost is implemented as:

$$c_{\text{tot}} = \sum_{p \in P} i(p)(C_{inv}(p)A(p) + OM_f) + \sum_{p \in P}\sum_{t \in T}(C_{run}(p,t) + C_{cycl}(p,t)) \tag{4.1}$$

The running costs for fueled technologies are defined by the fuel cost (C_{fuel} [€/MWh]), efficiency (η), and variable operation and maintenance cost (OM_v [€/MWh]). For the cases which allow the CCS technologies, the CCS technologies cost (C_{CCS} [€/MWh]) is also part of the running cost as:

$$\sum_{p \in P}\sum_{t \in T} C_{run}(p,t) = \frac{C_{\text{fuel}}}{\eta} + \frac{C_{\text{CCS}}}{\eta} + OM_v \tag{4.2}$$

As previous stated, the model implemented accounts for several constraints, such as constraints in terms of electricity generation, emissions, and storage. Firstly, the model requires that the demand be met at all times, and thus the load balance is guaranteed. The total electricity generated (g [MWh/h]) needs to be greater than, or equal to, the electricity demand (D^{el} [MWh/h]). The load balance is defined as:

$$\sum_{p \in P} g(p,t) \geq D^{el}(t), t \in T \tag{4.3}$$

[4] Combination of dispatch energy sources and VRESs. VRESs are composed of 12 different types of wind onshore power, wind offshore, and solar PV.

When electrification of the industrial sector is considered, the industrial demand is solely supplied by energy generated from electrolysers by electrolysis processes. Consequently, the H_2 storage is modeled as a function of energy stored (sto_{H_2} [MWh/h]), energy generated from electrolysers (x_{elec} [MWh/h]) and respective efficiency (η), and industrial demand (D^{H_2} [MWh/h]):

$$sto_{H_2}(t{+}1) = sto_{H_2}(t) + x_{elec}\eta(t) + D^{H_2}(t), t \in T \tag{4.4}$$

The model used in this thesis also set a cap on carbon emission (E_{cap} [$GtCO_2$]) as zero to obtain a system with high share of renewable energy. This means that the carbon emission (E [$GtCO_2$]) from the electricity generation must be zero:

$$\sum_{p \in P} \sum_{t \in T} E(p,t) g(p,t) \leq E_{cap} \wedge E_{cap} = 0 \tag{4.5}$$

eNODE also accounts for the intermittency of VRESs and for thermal cycling. As the regional model accounts for a high temporal resolution, it can easily capture the variability originated from a high VRESs share. Thus, the model implements energy storage technologies in order to solve the need for flexibility that an electricity system composed of a high share of VRESs requires. Mathematical descriptions concerning these constraints including investment of VRESs, thermal cycling, and energy balances for energy storage are thoroughly described in [12].

4.2 Monte Carlo Analysis

As explained in section 1.1, this thesis looks at identifying the different uncertainties which are associated with increasing the adoption of solar power. The different uncertainties are correlated to investment and fuel costs of different technologies. To capture possible future costs, different ranges of investment costs of both VRESs and energy storage technologies, as well as fuel costs of fueled technologies, were implemented in the model. As the parameters evaluated in this thesis were organized in a range of values, a Monte Carlo analysis was conducted to examine the sensitivity of different parameters by varying the investment cost and fuel cost of different technologies. The analysis ran with a uniform distribution, to ensure that all values had an equal probability of occurring.

It is important to note that this master's thesis does not attempt to forecast the future, but rather aims to understand which uncertainties promote, or prevent, the optimal share of solar power. As a result, this thesis evaluated the cost-effectiveness of different technologies and thus an extensive sensitivity approach was adopted for the whole range of parameters. Consequently, as all the parameters ran with a Monte Carlo analysis, different scenarios regarding an electricity sector composed of a high share of solar were obtained. The diversity of possible scenario was extremely important when it came to understand the factors that influence the increase in solar power share in the electricity sector. Thus, this master's study identified different trends, which can shape the composition of a future electricity sector.

4.2.1 Sensitivity Analysis

This master's thesis conducted an extensive sensitivity analysis of all the parameters studied. Sensitivity analysis is described by Saltelli *et al.* [56] as "the study of how uncertainty in the output of a model (model or otherwise) can be apportioned to different sources of uncertainty in the model input". Thus, conducting a sensitivity analysis suited the purpose of this study considering that it allowed the evaluation of how different uncertainties - investment and fuel costs - affect the solar power share while minimizing the total system cost.

4.3 Input Data

To more effectively answer the research question mentioned in section 1.1, this thesis added financial data to the pre-existing data in the model. The financial added data was included in two different forms, investment, and fuel cost. The data was rearranged in gaps of values varying between lower and upper limits, originally from different sources. The main input data used in this this can be seen in Tables 4.1 and 4.2.

Table 4.1: Main input data of this master's thesis - Technology investment cost added to the model.

Technology	Investment Cost		Reference
	Lower Limit	Upper Limit	
Solar PV [k€/MW]	200	800	[14]-[8], [15]
Wind Onshore [k€/MW]	800	1500	[14]
Wind Offshore [k€/MW]	1420	2140	[14]
Battery Storage [k€/MWh]	46	225	[14]
Battery Capacity [k€/MW]	40	250	[14]
H_2 Storage [k€/MWh]	1	11	[14]-[12]
Fuel Cell [k€/MW]	500	1100	[14]
Electrolyser [k€/MW]	350	700	[14]
Nuclear Power [k€/MW]	4000	6000	[16]-[17]

The lower limit of all the technologies was originally from the Danish Energy Agency (DEA) [14]. For some of the technologies, the upper limit suggested by DEA was relatively close to the lower limit which would hinder a rich variety of possible scenarios. Consequently, the upper limit from some of the technologies was based on other sources, which pointed to higher values.

The adopted upper limit for solar PV differed from the one suggested by DEA as their suggestion was remarkably low. Instead, the upper limit for the investment cost of solar PV, 800 k€/MW, was previously adopted by Atsmon and Ek Fälth [8] as their base case, which was retrieved from the mid-cost scenario projection presented by National Renewable Energy Laboratory's (NREL) Annual Technology Baseline (ATB) Database for 2018 [15].

The upper limit of wind onshore needed to be adjusted since the wind used in this thesis is 200[5] W/m^2, which has considerably larger turbines blades[6] than the wind used by DEA, and therefore the investment cost adopted is higher. The increase in the investment cost is justified by higher FLH, characteristic of the wind implemented in the model used in this master's thesis

In terms of H_2 storage investment cost, DEA suggested a very low upper limit. For this reason, a H_2 storage investment cost was assumed with an upper limit of 11 k€/MW, the default value in the model, which was earlier used in different papers, such [12]. Consequently, the lower limit of H_2 storage represents salt caverns, while the upper limit represents lined rock caverns.

The upper limit of investment cost for both wind offshore and fuel cell was modified so that the most probable value suggested by DEA was the middle value in the investment cost range used in this master's thesis.

When nuclear power investment cost was considered, the investment cost range was set to vary between 4000 k€/MW and 6000 k€/MW, as used previously by Hirth [16] and Brown and Reichenberg [17], respectively.

Table 4.2: Main input data of this master's thesis - Updated fuel cost. Data originally from different sources.

Fueled Technology	**Fuel Cost** [€/MWh]		**Reference**
	Lower Limit	**Upper Limit**	
Hard Coal	4.8	14.7	[18], [19]
Natural Gas	17.1	51.4	[18], [19]
Biomass	30	100	[19] -[20]
Biogas	63	163	[21]
Nuclear	6		[22]

The fuel cost was also implemented in the model as a range. These values are represented in Table 4.2.

The fuel costs of hard coal and natural gas were modified from a static value into a range between 0.5 and 1.5 of the default values in the model, previously used in studies such as [19]. The approach of ranging a static value into an interval of up 50% and down 50% was already used by Lehtveer *et al.* [18]. Consequently, this approach suited hard coal and natural gas fuel cost well, as this thesis does not aim to precisely predict what happens to these fuels, but rather to understand what the impact of these fuels getting cheap or expensive have on the electricity sector.

In terms of biomass fuel cost, the cost was set to a range that varies from 30 €/MWh, default values of the model, and previously used in [19], to the upper limit of 100 €/MWh, which is in accordance with Bolhàr-Nordenkampf [20]. Biogas is the result

[5] 200 W/m^2 refers to the ratio between the rotor swept area to the rated power of the turbine.
[6] Larger diameter.

of the gasification of solid biomass. This conversion has an efficiency of 70%. Additionally, it is necessary to account for the gasifier equipment costs. Consequently, biogas fuel cost ranged according to $\frac{BiomassFuelCost}{0.70} + 20$ [€/MWh] [21].

The nuclear fuel cost assumed in this study was in accordance with Lvque [22]. The fuel cost for nuclear power plants was set as constant, considering that the major uncertainty of these plants is the investment cost, which is tested in detail by doing a sensitivity analysis.

This master's thesis re-utilized most data, which was already implemented in the model (appendix A.3). The pre-existing data used in the analysis, in terms of annual electricity demand and demand profile for each technology, is taken from the projections made by ENTSO-E and their assumptions. The Portuguese electricity demand for 2050 is assumed to be 55.68 TWh, as proposed by ENTSO-E [57]. Additionally, most of the pre-existing economic data are retrieved from the World Energy Outlook by International Energy Agency IEA in 2014, which is presented in the appendix, see A.3. The pre-existing data also considered weather profiles [58]–[63].

4.4 Model Scenarios

To better address the research questions presented in section 1.1, this paper evaluates the possibility for the existence of both expensive batteries storage investment cost and the CCS technologies, as well as, an industry demand characterized by an increase in H_2 demand from electrolysis. Consequently, this thesis brings together four different scenarios, which are described in detail in Table 4.3.

Table 4.3: The four different case scenarios implemented in this thesis.

<table>
<tr><th>Scenario</th><th>Battery Storage Investment Cost [k€/MWh]</th><th>CCS</th><th>H_2 Demand</th><th>Runs</th></tr>
<tr><td>Base Case</td><td>46-135</td><td rowspan="2">x</td><td rowspan="3"></td><td>533[1]</td></tr>
<tr><td>Expensive Battery</td><td>135-225</td><td>467[1]</td></tr>
<tr><td>No CCS Technology</td><td rowspan="2">46-135</td><td></td><td rowspan="2">500</td></tr>
<tr><td>Industrial Demand</td><td>x</td><td>x</td></tr>
</table>

[1] Important to note that the base scenario ran 1000 times; Nevertheless, this thesis split the runs (results) according to the battery storage investment cost range. Consequently, the base scenario results accounted for 533 runs, while the expensive battery scenario considered 467 runs.

Each scenario has its own limitations which include both the accessibility of different technologies and the analysis of other sectors. For all the scenarios, the financial data remained constant and the total emission of CO_2 was set to zero. All the scenarios have the possibility to utilize nuclear power and VMSs, such as battery storage and H_2 storage. Additionally, a sensitivity analysis was conducted by varying the nuclear power investment cost. For this case, the model ran 500 times, and used the same data, both technical and financial, as well as the constraints, as used in the base case scenario.

4.4.1 Base Case

The base case scenario only includes batteries with investment cost ranging from 46 k€/MWh to 135 k€/MWh. This scenario also includes thermal power plants with the possibility of CCS technologies. There are two possibilities for dispatch power plants associated with CCS, which are associated with both coal and natural gas: bio-coal CCS and bio-natural gas CCS. This scenario also allows nuclear power plants and biofuels technologies.

4.4.2 Expensive Battery

This scenario was initially included in the base scenario, which ran 1000 times. Nevertheless, it was found that battery storage investment cost had a strong impact on the solar power share. Owing to this, this master's study, split the base scenario in two scenarios, varying according to the battery storage investment cost. One ranging from the lowest value (46 k€/MWh) suggested from DEA to the medium value (135 k€/MWh) - base scenario 4.4.1 - and other one covering values higher than the medium value and the highest value (225 k€/MWh) also suggested by DEA - expensive battery scenario.

4.4.3 No CCS Technology

This scenario excludes the possibility of CCS technologies. Yet, nuclear power plants remain an option in the electricity sector. Furthermore, biofuels gain greater importance in this scenario. Thus, this scenario investigates how the role of not allowing CCS technologies can impact the carbon neutrality of the electricity sector, in comparison with the system composition of the base scenario. Additionally, as in the base scenario, in this scenario battery storage investment cost is set in an interval varying between 46 k€/MWh and 135 k€/MWh.

4.4.4 Industrial Demand

Lastly, this scenario considers an addition of the H_2 demand of 15% of the total demand. The addition of H_2 demand is solely ensured by the energy generated from electrolyzer technologies. Furthermore, this scenario emphasizes how including an increase of H_2 production in the industrial sector will impact the electricity sector, by comparing it with the base scenario. In terms of battery storage investment cost, the same approach as adopted in the base and no CCS scenarios is used in this scenario, with battery storage investment cost higher than 46 k€/MWh but lower than 135 k€/MWh.

5

Results

This chapter presents the findings obtained to answer the research questions outlined in section 1.1.

Firstly, Monte Carlo analysis investigates the dependency of both generation mix and the system LCOE on solar power investment costs for the three scenarios with low battery storage investment cost presented in chapter 4. In addition, the energy storage technologies capacity is discussed below. Secondly, the load duration curve of dispatchable technologies for the base scenario is obtained for three different cases: high solar power share; high solar and wind power share; and high nuclear power share. The marginal electricity cost[1] and how that correlates to the electricity generation mix is investigated for each case. Lastly, a sensitivity analysis of the investment cost for nuclear power is presented to understand the nuclear power's impact on the electricity system.

5.1 Monte Carlo Analysis

The results presented here are mainly dependent on the investment cost of solar power and battery storage because these two parameters were found to have the highest impact on the solar power share. However, in the appendix (A.4.2), the impact of other technologies' investment costs on the electricity system is also presented.

5.1.1 Solar Power Generation

Solar power share is strongly influenced by the solar power investment cost, as it can be observed in Figure 5.1. Generally, the solar PV share increases with a reduction in solar power investment cost. Consequently, high solar PV share is linked to low solar power investment costs while a low solar PV share is associated with high solar power investment costs. From the graph, it is also possible to deduce that the solar PV share increases as the battery storage investment cost is lowered (from orange boxes to yellow boxes).

The two aforementioned trends suggest the existence of synergy between solar PV

[1] Cost of producing 1GWh extra of electricity.

and battery storage technologies. Apart from the low solar power investment costs, high solar power shares also benefit from low battery storage investment costs. An electricity system composed of a considerable amount of solar power lacks flexibility, which can be addressed by cheap battery storage systems. Thus, low battery storage investment cost also promotes an increase in solar power share.

Figure 5.1 depicts the range of solar power investment cost, which varies between 200 k€/MW and 800 k€/MW, divided into 12 subintervals of 50 k€/MW. For each of the scenario, the battery storage investment cost, at different solar power investment costs, is varied within each of the two ranges - 46 k€/MWh to 135 k€/MWh and 135 k€/MWh to 225 k€/MWh. In the base scenario, the average battery storage investment cost was 91 k€/MWh, while the cost, in the expensive battery scenario, was approximately 182 k€/MWh.

By looking at the base scenario (yellow boxes), it is possible to conclude that when solar power investment cost decreases from 800 k€/MW to 200 k€/MW, the solar power share increases by a minimum of 14% to a maximum of 88%. Regarding the different solar power investment costs, it is also possible to see that larger uncertainties - higher length of the probability boxes - are associated with cost varying between 400 k€/MW and 700 k€/MW. Thus, at low (200 k€/MW to 400 k€/MW) and high (700 k€/MW to 800 k€/MW) solar power investment costs, it is easier to predict what is happening in the system. When the solar power investment cost is higher than 700 k€/MW, the cost-optimal solar power share can not surpass 50% of the total electricity generation. On the other hand, when solar power investment cost goes bellow 400 k€/MW, the solar power share covers at least 50% of the whole electricity generation. When solar power investment cost is varying between 400 k€/MW and 700 k€/MW, there is huge uncertainty about what is happening regarding other technologies in the electricity sector.

In the expensive battery scenario (orange boxes), the solar power share is expected to increase from a minimum of 11% to a maximum of 77%, when the solar power investment cost is lowered from 800 k€/MW to 200 k€/MW. If comparing this scenario to what is happening in the base scenario, it is possible to conclude that for solar power investment costs higher than 400 k€/MW, the electricity system does not have the capacity of reaching solar power shares higher than 50%.

Finally, Figure 5.1 conveys that doubling the battery storage investment cost from 91 k€/MWh to 182 k€/MWh promotes a reduction in solar power share. When solar power investment cost is higher than 600 k€/MW, doubling the battery storage investment cost reduces, on average, solar power share by 11%. For solar power investment costs ranging from 350 k€/MW and 600 k€/MW, the reduction in solar power share is approximately 27%. Finally, when the solar power investment cost is lower than 350 k€/MW, doubling the battery storage investment cost can, on average, reduce the solar power share by 18%.

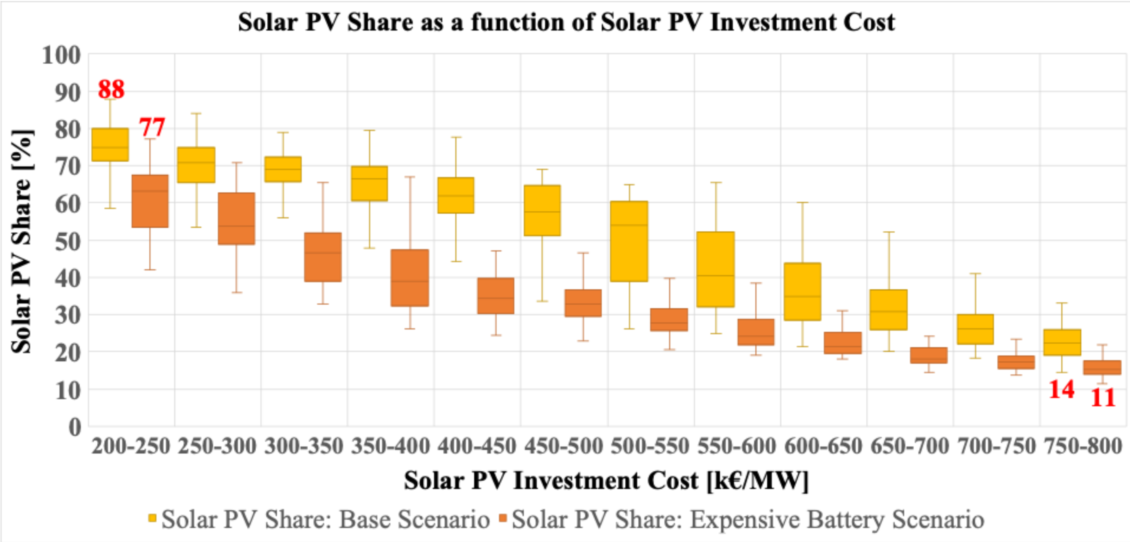

Figure 5.1: Probability of solar PV share according to different solar power investment costs for both base case and expensive battery scenarios. The boxes represent the 25% and 75% percentiles, while the middle line defines the median. The whiskers represent both the minimum and maximum shares. Furthermore, a comprehensive explanation how to interpret the graph is presented in appendix A.4.1.

5.1.2 Generation Mix

From the above findings, it is clear that a greater cost-efficiency of solar power share is associated with both low solar power and battery storage investment costs. Still, there is a need for looking at the entire electricity generation system to get a better overview of how other electricity generation sources cope with solar power, which is illustrated in Figure 5.2.

As solar power investment cost gets lower, nuclear power share is also lowered. More precisely, when the solar power investment cost goes down from 800 k€/MW to 400 k€/MW, the nuclear power share is lowered from supplying approximately one third of the total electricity generation (32%) to zero. This is caused by the fact that nuclear power is a baseload power plant. As a baseload power plant, nuclear power's flexibility is limited since it cannot easily change the output due to economical, technical, and security constraints. Thus, nuclear power plants are more cost-beneficial when running at full capacity for a year, considering that from an economic perspective, it is not justifiable to invest in these plants as intermediate technologies. For solar power investment cost greater than 750 k€/MW, nuclear power share exceeds the share of every other power plants composing the electricity sector. For this very reason, at low solar power investment cost (lower than 400 k€/MW), the electricity system does not have room to accommodate electricity generated by nuclear power. Consequently, solar power is complemented by other sources of electricity generation, such as wind power, fossil-fueled power plants with CCS technologies, and biogas power plants.

Wind power share is lowered by 15% from a maximum of 16.6 TWh/year, when the solar power investment cost drops from 800 k€/MW to 200 k€/MW. When the solar power investment cost is higher than 700 k€/MW, wind power is characterized by a higher share than solar power. As solar power becomes more costly, wind becomes cheaper than solar power and hence a better option for the system. For solar power investment costs varying between 500 k€/MW and 700 k€/MW, wind power is complementing the electricity generated from solar power. When solar power investment cost goes below 500 k€/MW, which represents solar power shares higher than 50%, wind power is outcompeted by solar power. At these solar power investment costs, even though solar power has lower FLH than wind power (appendix A.3), it is significantly cheaper than wind power and hence it is more cost-beneficial to invest in solar rather than in wind power.

From an annual perspective, both fossil-fueled power plants with CCS and biofueled power plants have an electricity generation close to constant at all solar power investment costs. This results from their nature of intermediate (fossil-fueled CCS technologies) and peak-load (biogas) power plants. These thermal power plants only exist in the system to complement other electricity generation sources rather than becoming the major sources of the system. Bio-natural gas CCS accounts for a share ranging from approximately 20% to 10%. Higher shares of bio-natural gas CCS are associated with times when the electricity system accounts for a higher share of nuclear power. As a baseload power plant, nuclear requires to be complemented by other electricity generation sources. This complementary is well suited by thermal power plants, such as fossil-fueled power plants with CCS technologies. Bio-coal CCS, despite of having lower running costs than bio-natural gas CCS, suits better the electricity system when there is a high need for full-load hours. Hence it accounts for a lower share in the system than bio-natural gas CCS, reaching a maximum of 5%, only when natural gas becomes more costly. Regarding biogas power plants, there is a constant share of electricity generation ranging between 1% and 2%, at any solar power investment cost.

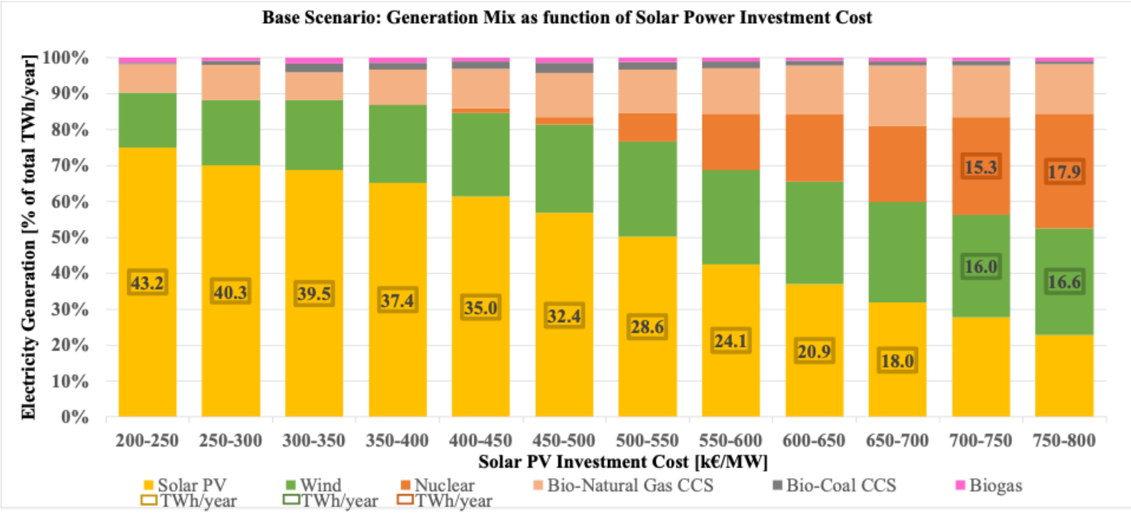

Figure 5.2: Generation mix of the base scenario, which represent the average of the runs within the same solar power investment cost span. Only data labels for technologies with higher share than solar power are included.

Figure 5.3 depicts the differences in generation mix regarding the three different scenarios: base, no CCS, and industrial demand. The results here presented assume battery storage investments costs varying between 46 k€/MWh to 135 k€/MWh, considering that it is of importance to evaluate how battery storage devices becoming cheaper impacts the cost-optimal share of solar power. Nevertheless, results for higher battery storage investment cost can be found in appendix (A.4.3 and A.4.4).

From the electricity generation perspective, solar power share differs between an electricity sector that allows CCS technologies and one which prohibits them. As it is possible to see in Figure 5.3, when solar power investment costs are higher than 400 k€/MW, the solar PV share is lower in the no CCS scenario (middle columns) than in the base scenario (left columns). At these investment costs of solar power, the balance between nuclear power and VRESs is changed in favour of nuclear and thus it is more cost-efficient to invest in dispatchable electricity generation sources, such as nuclear and biogas power plants, than in VRESs. The main reason is the lack of options for the system to invest in. With no option for CCS technologies, for solar power investment costs higher than 400 k€/MW, the system finds it more cost-optimal to increase the share of electricity generated from firm sources, which require less complement. However, when solar power investment costs are lower than 400 k€/MW, the solar power share in the no CCS scenario is, in fact, higher than in the base scenario. At these reduced solar power investment costs, together with the few options of electricity generation sources - solar, wind, nuclear, and biogas power -, it is more cost-efficient to invest in higher capacities of solar power rather than in other sources.

Generally, in the no CCS scenario, as previously mentioned, dispatchable power plants have major importance in the generation mix of the electricity system. Nuclear power plants co-exist in the system at solar power investment costs ranging from 250 k€/MW to 800 k€/MW. For solar power investment costs higher than

550 k€/MW, nuclear power plants account for at least 50% of the total electricity generation share and therefore becoming the major source of the whole system. Biogas, which is typically a peak-load power plant, increases its total share to 5% and hence acts, to some degree, more like an intermediate-load power plant. Owing to the evident importance of dispatchable technologies, wind power in the no CCS scenario, remain quite constant at all the solar power investment cost. For solar power investment costs higher than 700 k€/MW wind power is outcompeted by nuclear power. Additionally, when solar power investment costs are lower (<500 k€/MW), wind power is outcompeted by solar power.

The industrial demand scenario (right columns) accounts for similar shares of solar power as the base scenario. The main reason being is both scenarios having similar constraints. The only difference is that the industrial demand scenario accounts for the addition of the H_2 carrier demand, which does not result in major changes in the generation mix. Contrary to what happens in both base and no CCS scenarios, wind power has more importance in the system for higher solar power investment costs. More precisely, the added H_2 demand for electricity to power the electrolyzers can be successfully supplied by electricity from wind power, as a consequence of the suiting cost structure of a H_2 system with low cost of storage. When the solar power investment is higher than 700 k€/MW, wind power becomes the major electricity generation source of the whole system. This is the result of H_2 being relatively cheap in comparison to other technologies. H_2 storage at these low costs is able to provide important services in the system, which brings flexibility. Thus, as H_2 storage manages well the slower variations of wind power (relatively to solar power), cheap H_2 storage promotes the increase of wind power share in the system.

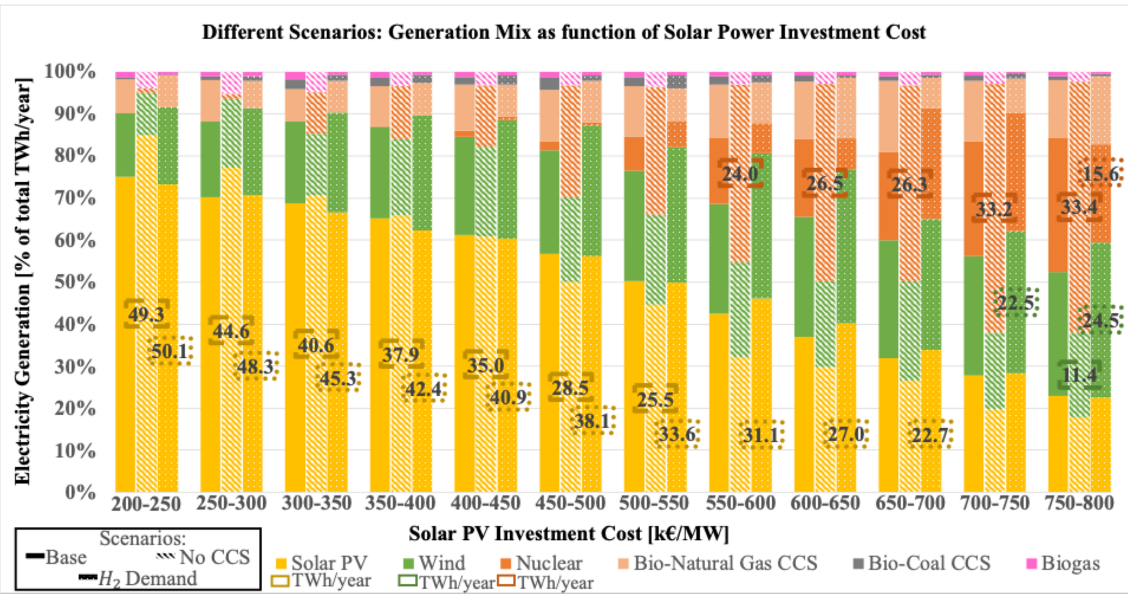

Figure 5.3: Generation mix of three scenarios: base, no CCS, and industrial demand scenario; which represent the average of the runs within the same solar power investment cost span. Only data labels for no CCS and industrial demand scenario are included, as well as only technologies with higher share than solar power are included.

5.1.3 System LCOE

Different scenarios are characterized by different parameters, which result in different generation mixes. Considering that the parameters - allowance of CCS and addition of industrial demand - were of importance, the system LCOE also varied according to different scenarios. Figure 5.4 shows how the system LCOE varies both for different solar power investment costs and different scenarios.

By comparing the three different scenarios, it is obvious that the no CCS scenarios account for the highest values of the system LCOE. The main reason being is that in the no CCS scenario the system is limited in the types of plants that can be invested in and thus less options results in higher system LCOE. As a result of less alternative for complement, nuclear and dispatchable power plants, like biogas, become the cheapest option. Nevertheless, even the cheaper option, nuclear power plants, as a baseload power plant, are expensive to install and to start to run, while biogas power plants in this scenario are responsible for a higher share of electricity generated, which make these plants more costly when they operate at longer duration in the year than what characterizes typical peak-load power plants. Thus, even thought not as a principal cause for the increase of the system LCOE, the extensive use of these plants also increases the system LCOE.

In regards to the industrial demand scenario, the system LCOE is lower than in the other scenarios. In this scenario, the lower system LCOE results from the added H_2 demand, which is more flexible than the base case scenario demand from an economic view, considering that H_2 can be stored for longer periods than electricity.

The difference between the system LCOE in the three scenarios is constant for all solar power investment costs. This means that CCS technologies and industrial demand is important for the system LCOE, regardless the investment cost of solar power. Higher capacity undoubtedly results in lower system LCOE. Furthermore, it is possible to see that the value of CCS technologies is approximately 4 €/MWh, at any solar power investment cost. On the other hand, the value of an addition of H_2 demand is around 2 €/MWh, which could be higher if electrolyzers, which are needed to convert electricity in H_2, would become cheaper.

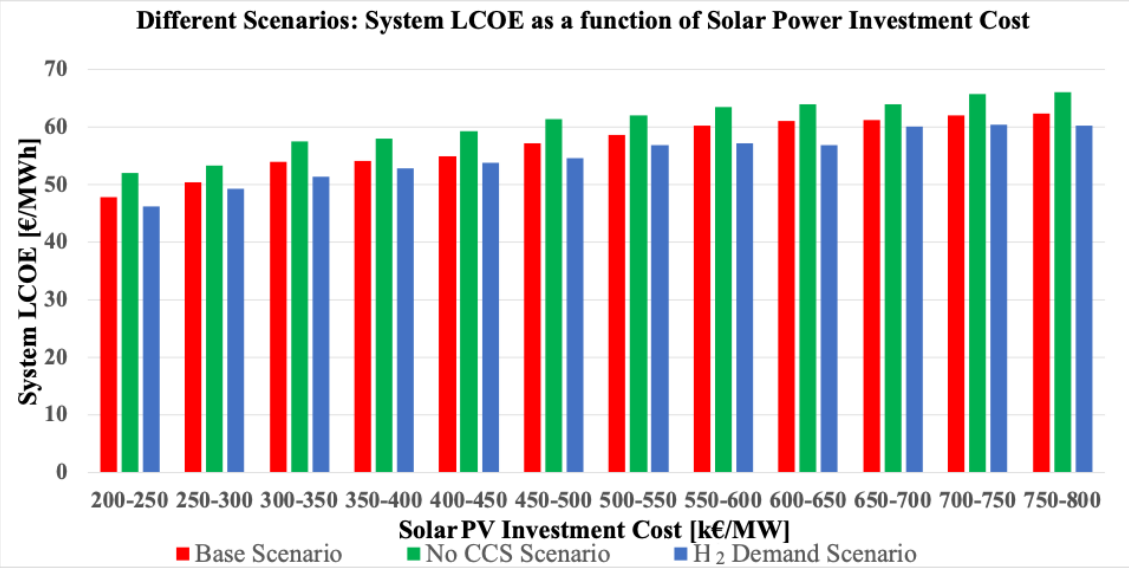

Figure 5.4: System LCOE of three scenarios: base, no CCS, and industrial demand scenario; which represent the average of the runs within the same solar power investment cost.

5.1.4 Energy Storage Capacity

An electricity system with a high share of solar power requires larger amounts of flexibility to shift the electricity generation from the sunny hours to evenings and nights, which can be addressed by energy storage technologies. Figure 5.5 shows how varying solar power investment costs, which are associated with different generations mixes, promote differences in energy storage capacities.

Generally, the total energy storage capacity increases as the solar power investment cost is also lowered. This reduction varies for different scenarios. In the base case, the battery storage capacity increases from 24 GWh to 72 GWh, as the solar power investment cost is lowered from 800 k€/MW to a minimum of 200 k€/MW. For the same decrease in terms of solar power investment cost, in the no CCS scenario, the battery storage capacity is increased by 65 GWh reaching a maximum of 85 GWh, while in the industrial demand scenario, the increase in the battery storage capacity is approximately 54 GWh (until a maximum of 73 GWh).

H_2 storage also changes its role in the electricity system according to different scenarios. In the base scenario, H_2 storage is insignificant, considering that there is no major need for storage. It is important to note, that even though H_2 storage is relatively cheap, this technology is characterized by poor efficiency in converting electricity-H_2-electricity. Also, both electrolyzers and fuel cells were considered in this thesis as expensive technologies (when comparing e.g, with battery storage systems). Consequently, H_2 storage only becomes cost-efficient at times with significant need for storage. The no CCS scenario results in higher capacities of H_2 storage than the base scenario. The main reason being is that in the no CCS scenario the electricity system is limited in terms of choices of producing electricity. Hence at times when biogas power plants are more costly, the system invests in both electrolyzers which run during sunny times and fuel cells. Finally, H_2 storage holds prominent importance in the electricity system of the industrial demand scenario. This is due to the fact that is more cost-efficient to overinvest in electrolyzers and build storage, to guarantee that H_2 demand does not need to be met by electricity directly in each hour.

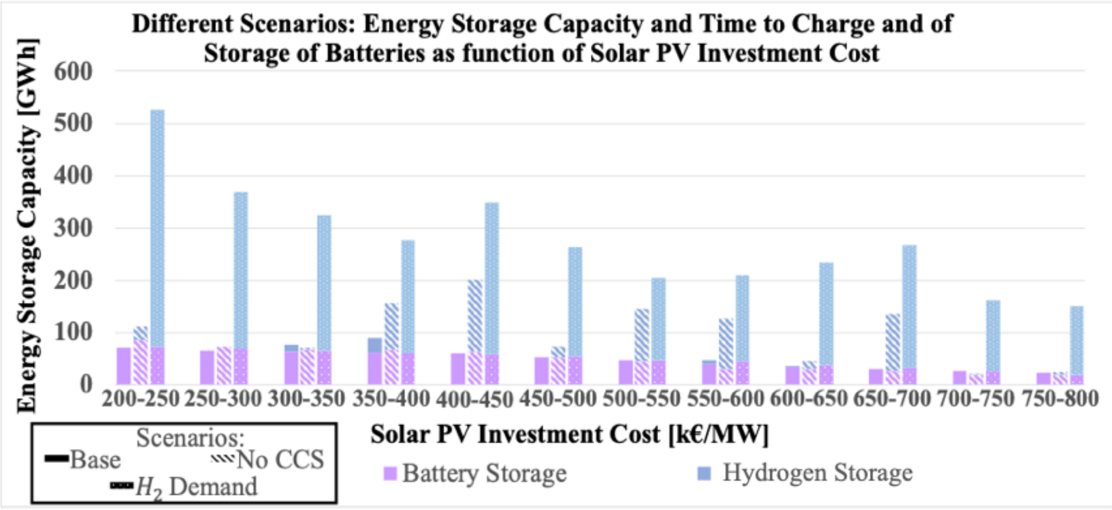

Figure 5.5: Energy storage technology capacity of the three scenarios: base, no CCS, and industrial demand; which represent the average of the runs within the same solar power investment cost.

5.2 Three Electricity System Cases

For the base scenario, three different cases were studied in detail. These three cases are examples of different electricity systems, which aim to show large differences between the parameters studied in this study:

- A case with the highest solar power share;
- A case with high solar and wind power share - composed of 40% solar and 40% wind power;
- A case with the highest nuclear power share.

For these three cases, the differences regarding the load duration curves, generation mix, and the marginal electricity cost were investigated. The specific input data - technologies' investment and fuel cost - for these three cases is presented in appendix (A.4.2.2).

When the solar power share accounts for 88% of the electricity sector, - Figure 5.6 (graph a) -, the system is both complemented by bio-natural gas CCS and biogas power. The same happens when the electricity system is composed of 40% solar power share and 40& wind power share - Figure 5.6 (graph b). The main similarity between the load duration curve of these two cases is that both cases are composed of a high share of renewables, which puts aside the need for baseload power plants, such as nuclear power.

In the highest solar power share case - Figure 5.6 (graph a) -, bio-natural gas CCS is running approximately 3003 hours in a year, with 2628 hours running at full-load of 0.2 GW, while in the high solar and wind power share case - Figure 5.6 (graph b) -, bio-natural gas CCS is running approximately 5736 hours in a year, with 1503 hours running at full-load of 3 GW. This means that the generation from intermediate-load power plants, such as bio-natural gas CCS, is higher in the high solar and wind power share case than in the highest solar share case, to compensate for the moments when both solar and wind are operating with low power due to poor weather conditions. Still, as there are few hours with low VRESs power generation, the required time for bio-natural gas CCS technology to run at its highest capacity is limited. Biogas power plants are extremely important in electricity systems composed of a high share of both solar power and VRESs, considering that these plants, as a peak-load power plants, are the cheapest option when there is only a need for low hours at full-load. These technologies manage the peaks in demand, which cannot be addressed by bio-natural gas CCS technologies, which are already running at maximum output. Likewise to bio-natural gas CCS, biogas power runs for higher time in the high solar and wind power case (5736 hours) than in the highest solar power share case (3003 hours), in order to compensate for lower hours of running at full capacity in the high solar and wind power share case.

If the electricity system is composed of 69% of nuclear power, - Figure 5.6 (graph c) -, it is possible to see that the net load curve (excluding nuclear power), is similar to the other two cases. This means that, in spite of the electricity system being composed of a major share of VRESs or nuclear power, there is an intrinsic need for complementary provided from fossil-fueled power plants with CCS and biogas power plants. The main difference between the three cases is that in the highest nuclear power share case, nuclear power is responsible for 69% of the total generation. Hence as a baseload power plant, it requires to be complemented by other thermal power plants. Consequently, the most significant technologies, in terms of meeting the demand, are CCS technologies. Bio-coal CCS, is the cheapest option (in comparison with bio-natural gas CCS and biogas) to run larger hours in a year at full-load capacity, which suits the need of nuclear power plants being complemented. As the bio-coal CCS runs for approximately, 3075 hours in a year at full capacity of 5 GW, bio-natural gas CCS, in the highest nuclear power share case, runs for lower hours at full capacity (1130 hours), when compared with the other two cases. Additionally, at times when more power is needed than what is produced by nuclear, bio-coal CCS, and bio-natural gas CCS, biogas power plants can contribute to filling this void.

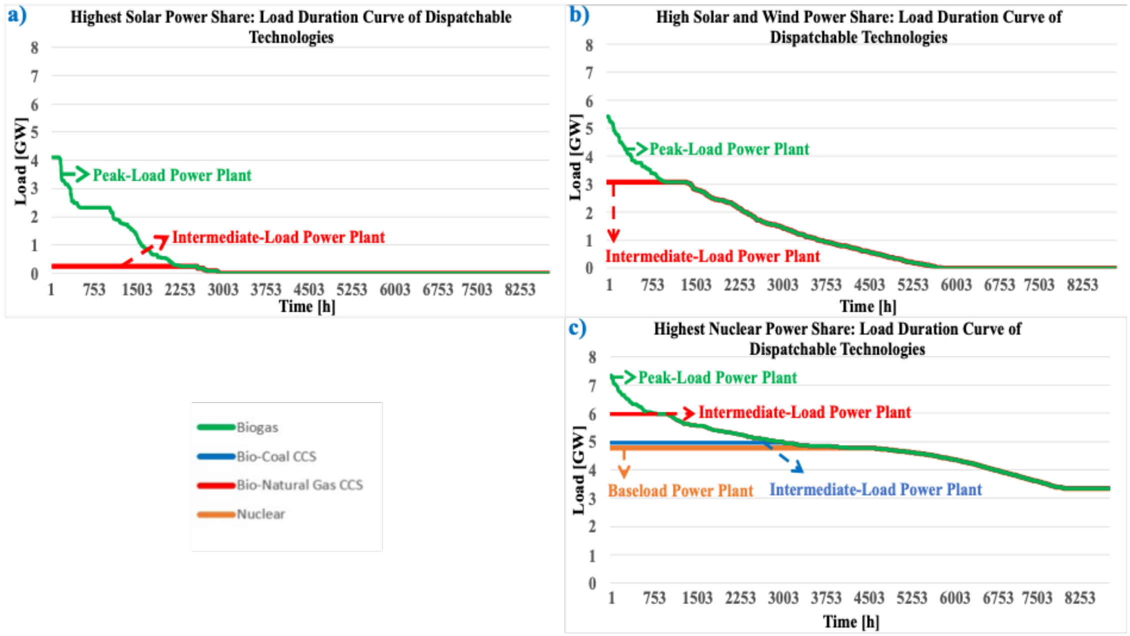

Figure 5.6: Load duration curve of dispatchable technologies for different shares regarding solar PV, nuclear power, and VRESs. The graph a represents the case with the highest solar power share (88%); The graph b) represents the case with high solar and wind power share (40% each); The graph c) represents the case with the highest nuclear power share (69%).

The generation mix of each case is illustrated in Figure 5.7, which describes the variety in the electricity system composition regarding the share of solar power, nuclear power, and VRESs.

As Figure 5.7 indicates, in the highest solar power shares case, the system only needs to be complemented sporadically, which suits biogas power plants very well due to their peak-load nature. In an electricity system composed of a solar power share of 88%, it is common to have hours when the generation exceeds the demand and hence the surplus goes into charging the batteries. Batteries guarantee 30% of the annual electricity demand. The same happens with an electricity system composed of high solar and wind power share. In case of high solar PV and wind power share, the system is greatly accounted for by bio-natural gas CCS technologies and biogas energy sources. Regarding energy storage technologies, 8% of the annual consumption is guaranteed by battery storage. At long periods of wind, excess wind power is stored. Consequently, H_2 storage, which better handles wind fluctuations, is responsible for approximately 0.5% of the total annual consumption.

On the contrary, in the highest nuclear power share case, the system is mainly composed of nuclear power, which results in other electricity source technologies being outcompeted. Yet, there are times when the system needs help to successfully meet higher demands. In this case, the system has little room for VRESs (when compared with the previous two cases) due to their intermittency, and thus dispatchable power plants, such as fossil-fueled thermal power plants with CCS technologies and biogas power plants, better complement nuclear power generation.

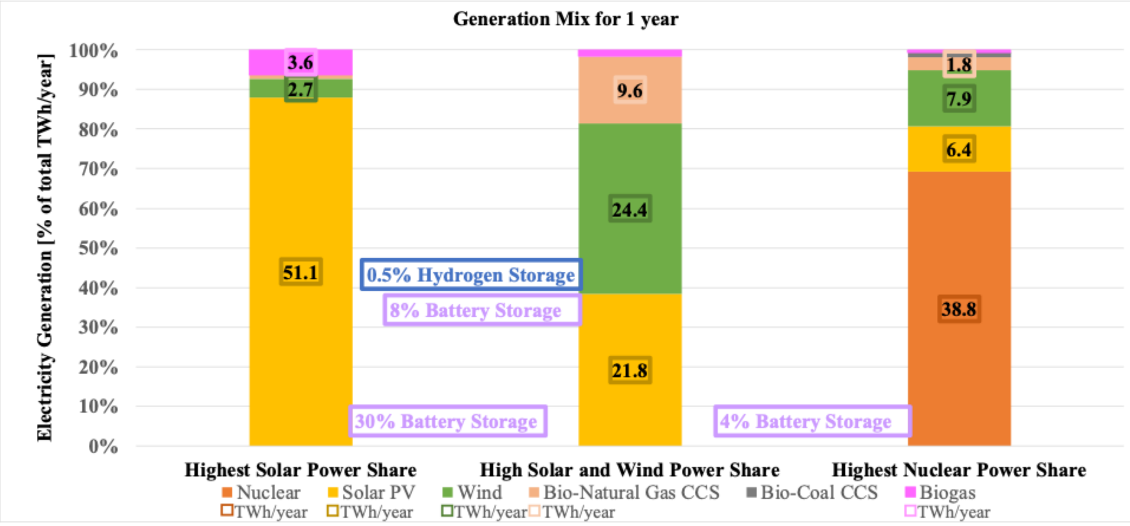

Figure 5.7: Electricity generation mix and energy storage capacities varies with different shares of solar, nuclear, and VRESs. The data labels for sources with lower than 1% of the total generation were excluded.

Regarding the generation mix, seasonal differences can also influence the composition of the system. For each case, both the first three weeks of January and August were considered when exploring the differences between winter and summer, respectively. The differences in the generation mix between winter and summer result in differences regarding the marginal electricity cost.

Figures 5.8, 5.9, and 5.10 depict that the total daily demand is clearly higher during winter than during summer, which can be explained by the fact that in the summer there is not the same need for heat technologies and light to compensate for the dark and cold days prevalent during winter. Also, the daily demand is higher during the day than the night, with peaks both on weekdays and also between the work hours. Winter seasons are characterized by higher peaks in solar power generation, considering that this type of solar panels (PV) decrease their efficiency when exposed to high temperatures (summer).

Figures 5.8 and 5.9 illustrate that for electricity composed of a high share of VRESs, regardless of the season, a big part of the electricity generation is powered by solar power. The functionality of the system is also strongly dependent on battery storage systems, as they store the surplus of electricity generated to later use. In the highest solar power share, during winter - Figure 5.8 (graph a) -, the system also includes complements such as wind power and biogas power, which well fit situations when the need for the complement is only occasional. In the high solar and wind power share case - Figure 5.9 -, the wind goes from being only a complement to being the major electricity source of the system. Additionally, due to the existence of long periods of high wind, the excess can be stored in fuel cells for later use. To compensate the times when both solar and wind are operating at low power, the complement, despite of including biogas power plants, also includes CCS technologies.

In the summer, CCS technologies and biogas are partly replaced by higher generation of solar power. More precisely, in an electricity system composed of 88% of solar power share, in the summer - Figure 5.8 (graph b) - the synergy composed of solar power and batteries solely guarantees the functionality of the electricity sector. The same synergy also plays an important role during the summer in an electricity system composed of high solar and wind power share - Figure 5.9 (graph b). However, this synergy only replaces the peak power generated, during the winter, by biogas power plants. This is explained by the fact, that there is an inherent complementary provided by CCS technologies, that compensate periods when both solar and wind power are not being generated at required levels to meet the demand.

When the electricity system composed of a high share of nuclear is considered - Figure 5.10 -, 69% of the total electricity generation originates from nuclear power. Consequently, the generation mix of this case differs from the previous two, which is explained by the fact that nuclear power as a base load power plants, is better complemented by other thermal power plans than VRESs. In both seasons the scarce power generated from VRESs is instantaneously used, considering that the high importance of thermal power plants in this type of electricity system limits the role of VRESs due to their inherent intermittency.

Regardless of the electricity system's composition, the marginal electricity cost is lower during the summer than during the winter. Owing to this, higher marginal electricity cost is associated with cold months - winter -, considering the inherent need of the system being complemented by dispatchable technologies - fossil-fueled power plants with CCS and biogas power plants -, which have a considerable high start and running costs. However, as there is a constant need for bio-natural gas CCS to complement an electricity system composed of 40% of solar power share and 40% of wind power share - Figure 5.9 -, the seasonal differences regarding the marginal electricity cost are not accentuated as depicted in Figure 5.8.

During the summer, as possible to see in Figures 5.8 and 5.9, due to peaks in solar power generation, the systems extensively use battery facilities which reduces the marginal electricity cost. Still, at times of excess of solar power generation, the system is very likely to curtail some solar power and the marginal electricity cost gets absolutely low, close to zero.

In an electricity system composed of high share of nuclear power - Figure 5.10 -, despite the marginal electricity cost being also lower during the summer than during the winter, the summer does not experience such low marginal electricity costs as electricity systems composed of high share of VRESs. This is a consequence of the system being composed of 69% of nuclear power, which as a baseload power cannot easily change its output, considering different economical, technical, and security constraints. Additionally, nuclear power puts aside the need for high levels of electricity generated from VRESs. During times of extra need of power generated, the system prefers to invest in bio-coal CCS instead of in more VRESs' capacity, which undoubtedly is associate with higher marginal electricity cost than the marginal electricity cost associated with VRESs.

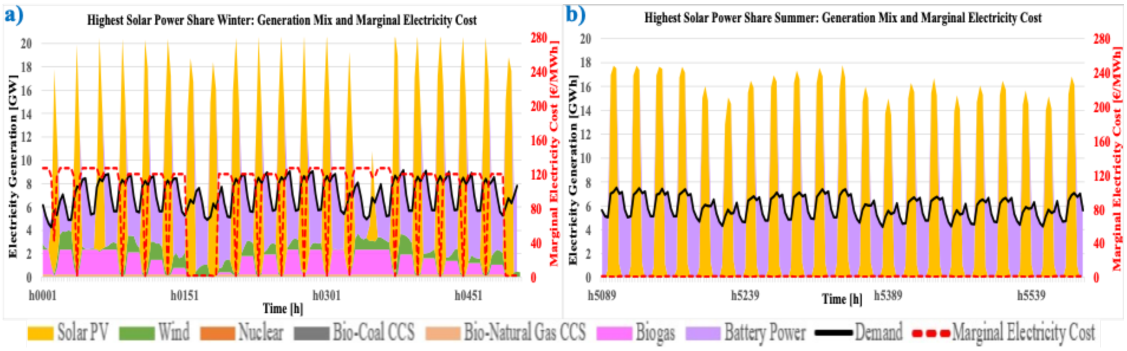

Figure 5.8: Seasonal generation mixes and marginal electricity cost for the highest solar power share case. Graph a) depicts the dispatch graph and marginal electricity cost of the first three weeks of January; Graph b) illustrated the dispatch and marginal electricity cost of the three first weeks of August.

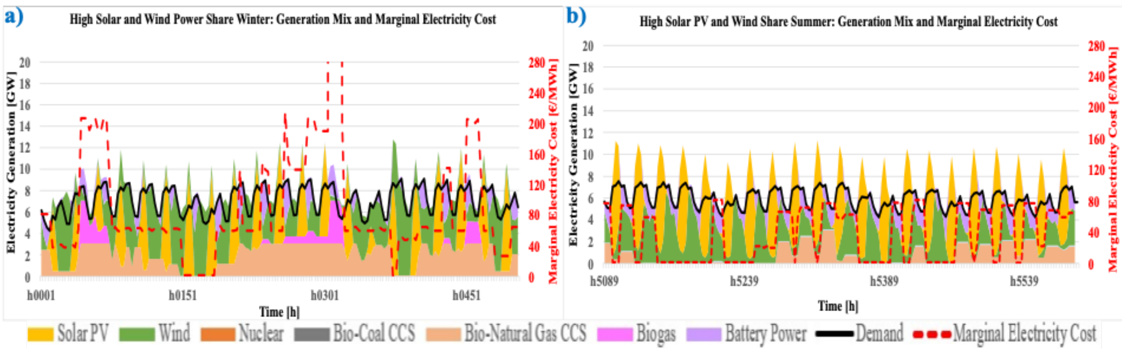

Figure 5.9: Seasonal generation mixes and marginal electricity cost for the high solar and wind power share case. Graph a) depicts the dispatch graph and marginal electricity cost of the first three weeks of January; Graph b) illustrated the dispatch and marginal electricity cost of the three first weeks of August.

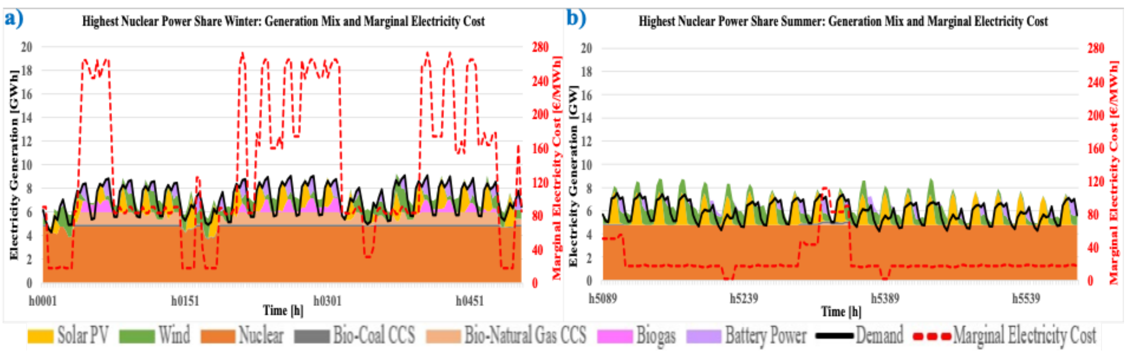

Figure 5.10: Seasonal generation mixes and marginal electricity cost for the highest nuclear power share case. Graph a) depicts the dispatch graph and marginal electricity cost of the first three weeks of January; Graph b) illustrated the dispatch and marginal electricity cost of the three first weeks of August.

5.3 Sensitivity Analysis: Nuclear Power Investment Cost

The results presented above account for a constant nuclear power plant investment cost of 4124 k€/MW. However, as few nuclear power plants are built due to different societal concerns (proliferation) and energy sustainable perspectives, the investment cost of these power plants becomes uncertain. In this sensitivity analysis, the electricity system is modeled with a nuclear power investment cost of between 4000 k€/MW and 6000 k€/MW. It was investigated how either lowering or increasing investment costs can influence different shares (solar, wind, and nuclear) and the system LCOE. The results are presented through a normalized nuclear power investment cost, which varies between 0.8 and 1.2, where 1 corresponds to 5000 k€/MW, which corresponds to the middle value.

The impact of the nuclear power plant investment cost on the share of different electricity generation sources is shown in Figure 5.11. It is possible to see that nuclear power is outcompeted when its investment cost is above 5250 k€/MW (1.05), which means that the system does not have room to accommodate nuclear power. An increase of nuclear power investment cost from 4000 k€/MWh to 5250 k€/MW results in an increase of solar power share from 42% to 46%. At the same values, the wind power share is increased from 27% to 34%. However, even though the VRESs share increases as a consequence of nuclear power becoming more expensive to be invested in, the increase in VRESs share is not as much as could be expected. This can be explained by the fact that the investment cost of VRESs remains quite constant for a nuclear power investment cost between 4000 k€/MW and 5250 k€/MW (0-1.05) (see appendix A.4.5). Consequently, apart of VRESs share being stimulated by higher nuclear power investment cost, it is also strongly dependent on the VRESs investment cost.

Varying the nuclear power investment cost does not impact the system LCOE, regardless of the impact on the VRESs share. In fact, different nuclear power investment costs do not influence the results in terms of system LCOE. As system LCOE remains constant at all the nuclear power investment costs, electricity systems characterized by different nuclear power investment costs are equivalent from the model perspective.

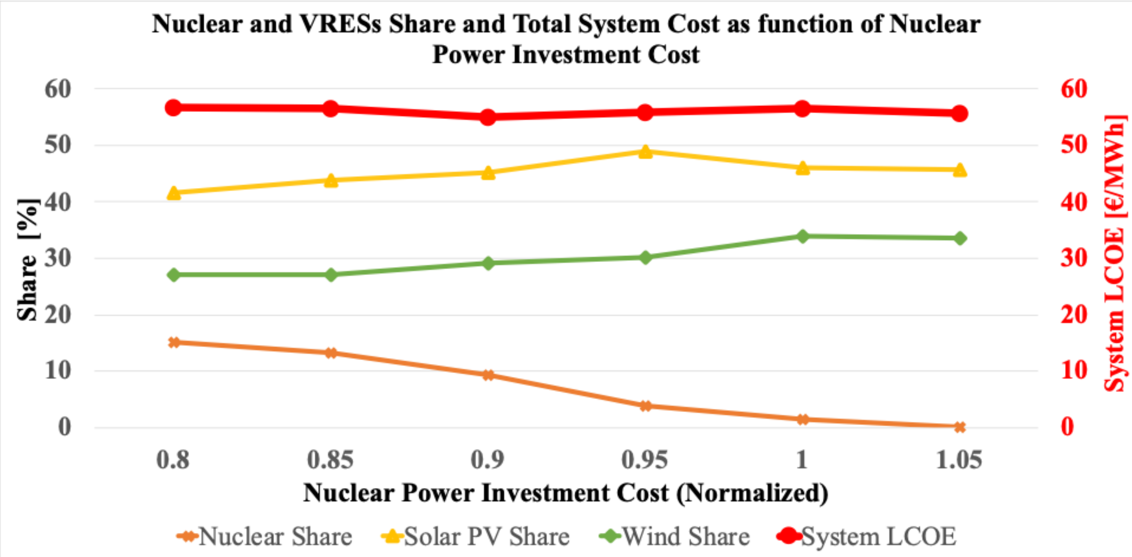

Figure 5.11: Sensitivity analysis on nuclear power plant investment cost and the impact on solar PV, wind, and nuclear power share, as well as on the system LCOE. Only results for nuclear power investment cost varying between 4000 k€/MW and 5250 k€/MW (0.8 and 1.05, if considered the normalized form) are represented, considering that nuclear power is outcompeted when its investment cost surpasses 5250 k€/MW.

6

Discussion & Future Work

This chapter discusses the findings of section 5. Further, it contrasts this master's thesis' findings to previous findings in the previous studies described in section 3.3. Finally, the limitations of this master's thesis are also discussed together with suggestions for future work.

6.1 The Value of Solar Power

Solar power investment cost was found as being the major uncertainty of solar becoming the major electricity supplier in the electricity system. Battery storage investment cost was also identified as having a prominent role in determining the solar power share. More precisely, this master's thesis found that doubling the battery storage investment cost from 91 k€/MWh to 182 k€/MWh promotes a reduction in solar power share by an average of 18%. Consequently, high solar power share also benefits from lower investment cost of battery storage systems, which emphasizes a synergy between these two technologies. In essence, lower solar PV investment costs promote an increase in solar power generation. Higher solar power shares require short-term flexibility solutions to guarantee a functional electricity system. This calls for *shifting* solutions as storage capacity, a characteristic of battery storage systems. Battery storage technology is primarily stimulated by EVs. Nevertheless, and if the solar power market continues to grow, which is strongly correlated to low solar power investment costs, the battery storage technology development is also likely to be promoted by higher solar shares.

This master's study also depicted some differences regarding the generation mix. Intermediate-load peak power plants, such as bio-natural gas and bio-coal CCS, and peak-load power plants, such as biogas, are found as having an electricity generation close to constant for any solar power investment cost. This is explained by the fact that these types of plants, which have considerable high running costs, better fit the system only as a complement and hence they are needed about as much in a solar dominated electricity system as in a system with high nuclear and wind power shares. In none of the cases considered in this thesis, electricity from pure biomass was generated. The main reason is that biomass is outcompeted by the fossil-fueled power plants with CCS and hence is never cost-efficient at any of the technologies' investment and fuel costs considered in this thesis.

Wind power was found to co-exist with solar power at any solar power investment cost. Even though wind has higher FLH than solar power, the system only gets a higher share of wind power when the solar power investment cost is higher than 700 k€/MW.

Seasonal differences in generation mix also result in differences regarding the marginal electricity cost. The marginal electricity cost is lower in the summer than during the winter, considering summer's favorable weather conditions for solar power generation. During the hot months, there are times with vast electricity production of solar power, which at times is either stored or curtailed. As a consequence, the marginal electricity cost is lowered. More precisely, when the electricity system curtails solar power, the marginal electricity cost goes down to low values, approaching zero.

6.1.1 Special Parameters: CCS Technologies, Industrial Demand, and Nuclear Power Investment Cost

Not allowing CCS technologies in the electricity system results in a lack of options for the system to invest in. Hence when solar power investment costs are higher than 400 k€/MW, it is more cost-efficient to invest in nuclear and biogas power plants, considering that these sources need less complement than solar power (and VRESs in general). Yet, when the solar power investment cost is reduced to values lower than 400 k€/MW, this trend is reversed. As the solar power investment cost is relatively low, for the same electricity demand, it is cost-beneficial to increase the capacity invested in solar than in other technologies. Removing options for electricity generation sources always results in higher system LCOE and consequently, the system LCOE under these restrictions increases by 4 €/MWh - CCS technologies' value.

An addition in H_2 demand by 15% of the total electricity demand, does not significantly change the composition of the electricity sector. Yet, when combining the electricity and industry sectors, it is possible to see that wind power is extremely important at high solar power investment costs (>700 k€/MWh if considered industrial demand scenario). This is a consequence of the added H_2 at low costs being able to provide great flexibility to the system, which well handles the variation of wind power and thus promotes wind power share to increase. H_2 storage works both as a *complement* and *absorbing* solution. An increase in industrial demand for H_2 lowers the system LCOE by 2 €/MWh - industrial demand's value.

On the contrary, nuclear power, in spite of influencing the shares of both solar and wind power, does not impact the system LCOE. Nuclear power plants only fit the electricity system at times when solar power needs more than being sporadically complemented, which is associated with greater solar power investment costs (>400 k€/MW if considered the base scenario). Additionally, regardless of other technologies' investment costs, the electricity system does not accommodate power originates from nuclear, when nuclear power investment cost surpasses 5250 k€/MW. At these costs, nuclear power is outcompeted by other electricity generation sources.

6.2 Comparison with Previous Studies

Frew *et al.* [5] suggest that in 2050, the total electricity generation in USA may be composed of 55% solar power, which is in accordance with the findings of Cole *et al.* [55]. On the contrary, this master's thesis found that, for a low investment cost in solar power (200 k€/MW) and batteries (91 k€/MWh), the electricity system can be composed of 88% solar power. Additionally, Frew *et al.* [5] describe that an increase in solar share in the electricity system leads to a reduction in the electricity price. In the same way, this master's thesis also witnessed that the marginal electricity cost becomes lower for higher solar power shares in the system, which is strongly associated with moments of either energy stored in batteries or electricity curtailment.

In accordance with Victoria *et al.* [6], this master's study also suggests that batteries are essential for maintaining a functional electricity system composed of a high share of solar PV in a cost-efficient way. In regards to H_2 storage, this master's study found that in addition to being a good fit for the power fluctuations commonly experienced from wind power, H_2 storage is also important at times when VRESs constitute the majority of the system requiring storage, if biofuels are expensive, or there is an increase in the H_2 carrier demand.

Additionally, this master's thesis agrees with Schlachtberger *et al.* [7], by demonstrating that when the battery storage investment cost is on average 91 k€/MWh, the system LCOE cost decreases linearly from 60 €/MWh to 48 €/MWh, while the solar power investment cost is lowered from 800 k€/MW to 200 k€/MW.

This master's thesis also looks at the system LCOE like Atsmon and Ek Fälth [8] do. The authors found that lower investment cost of both solar power and battery technologies have a large impact on the system LCOE. In the same way, this master's thesis found that by decreasing the solar power investment cost from 800 k€/MW to 200 k€/MW, for a battery storage investment cost, on average, lower than 91 k€/MWh, the system LCOE is lowered by 24%. Furthermore, when a higher amount of H_2 demand is accommodated in the electricity system, the system LCOE can reach a minimum of 46 €/MWh. The marginal electricity cost is lower for high solar PV generation, which this thesis shows is being caused by low solar power and battery storage investment cost. For an electricity system composed of high share of solar power, due to the excessive electricity storage and curtailment, the marginal electricity cost can approach zero during periods of several weeks during the summer season.

Finally, Villar *et al.* [9] suggest that at the residential level, the existence of synergy between solar power technologies and batteries can promote the acceptance of solar power in the electricity system. This thesis also confirms the importance of this synergy, albeit at a utility application, by solving the mismatch of demand profiles and solar PV generation.

6.3 Limitations & Future Work

From the analysis performed by this thesis, it is clear that there are still some limitations that could be addressed in future research.

In Monte Carlo analysis, only a uniform distribution was used. Using other types of distribution could impact the results. By doing so, it could be set which uncertainties, in regards of both investment and fuel cost, would be more probable, on the contrary to what took place in this thesis, with equal probability for any cost. More specifically, the average results, regarding the cost estimations, would be more accurate. Nevertheless, this would also depend on how precise the estimations on the distributions would be.

This master's thesis also did not investigate the land availability in regard to VRESs implementation in such detail, which undoubtedly would be an interesting parameter. Land availability could be a limited factor regarding suitable places for VRESs and thus the absolute amount of capacity of a certain VRESs.

Including the possibility of inter-regional transmission could also influence the generation mix and hence the system LCOE. Allowing transmission would first of all reduce the need for large investments in a specific geographical location. Since the investment would be distributed by different areas and not concentrated in a specific one, the system LCOE would likely be lower. On the other hand, transmission could, to some extent, reduce the share of solar generation in the electricity sector. The main reason is the possibility of transmission which promotes an increase in wind generation since it smoothens wind fluctuations.

In regard to CO_2 emissions, this study set a cap of zero total emissions. Nevertheless, including a cap that is either positive or negative would evoke other electricity system compositions. For instance, a positive cap of CO_2 emissions, would allow fueled power plants to run without being associated with CCS technologies. It would be expected that natural gas would become more important than coal in this scenario, considering that natural gas power plants are intermediate-load power plants. This would decrease the system LCOE. Contrary, if the cap would be set as negative, the CCS technologies would go from complement electricity generation sources to one of the major sources of the electricity system and hence the system LCOE would get higher due to their high investment and running costs.

The eNODE model, as a green-field cost optimization model, did not look at the current electricity sector. Nevertheless, including already installed capacity in the system, e.g. hydropower, could impact the future electricity composition, by reducing the already high need for the synergy composed of solar power and batteries.

Finally, this master's thesis just considered two sectors namely electricity and, albeit in not such detail, the industry sector. At the same time, the demand in this study was defined as exogenous to the model and inelastic. Yet, the electrification of other sectors, or a change in societal behavior, would impact the electricity demand. Consequently, studying the possibility of coupling these different sectors could also be of importance. As an example, in the case of electrification of the transport sector, changes in the electricity grid can be expected. EVs require electricity to be charged and thus the electricity demand would increase. However, EVs are also likely to stimulate an increase in prosumers and therefore less electricity from the grid would be used. EVs would be expected to reduce the need for stationary batteries, as the vehicles in itself works as a battery. Thus, due to the cheap battery storage systems that EVs incorporate, these vehicles would result in higher flexibility of the electricity system for accommodating higher shares of VRESs.

7
Conclusion

This master's thesis has outlined which uncertainties are associated with solar becoming the major electricity generation source in the electricity system in 2050 in a country with favorable conditions for solar power generation, such as Portugal. This study found that:

- Solar power becomes the major electricity generation source of the electricity sector when **1)** the battery storage investments cost is, on average, lower than 91 k€/MWh; **2)** the solar power investment cost is lower than 650 k€/MW.
- Solar power investment cost was found to be the major uncertainty for increased dependence on solar power in the electricity sector. Still, low battery storage investment costs stimulate an increase in solar power generation. Nuclear power plant investment costs also influence the solar power share.
- The system LCOE is lowered as a result of the increase in solar power share. When solar power investment cost is reduced from 800 k€/MW to 200 k€/MW, the system LCOE is reduced by 2% per every 50 k€/MW, to a minimum of 48 €/MWh.
- The increasing dependence on solar power in the electricity sector is promoted by, and also promotes, the use of battery storage to ensure the load balance. At times when the demand cannot be ensured by only solar PV and the excess of energy stored in the batteries, CCS technologies and biogas power plants become important, due to their intermediate and peak-load power plant nature. Nuclear power plants become important at solar power investment cost higher than 400 k€/MW, due to the intrinsic need for more constant output generation provided by these baseload power plants.
- For solar power investment costs higher than 700 k€/MW, wind power starts to account for a higher share in the electricity sector than solar. At solar power investment costs ranging between 700 k€/MW and 500 k€/MW, wind power is complementing solar power generation. Due to the major difference in the investment cost of the two VRESs, wind power is partially outcompeted by solar PV, at solar power investment costs varying between 500 k€/MW and 200 k€/MW, and thus at high solar PV share.

Doubling the battery storage investment cost from 91 k€/MWh to 182 k€/MWh decreases the solar power share by 18% on average. Forbidding CCS technologies stimulates the solar power generation, as long as the solar power investment costs are lower than 400 k€/MW. Nevertheless, the system LCOE is higher in the absence of these technologies, increased by a total of 4 €/MWh. The main reason for the increase is a decrease in options available in the system and an increasing dependence both on nuclear and biogas power. An exogenous demand for H_2 encourages an increase in wind power generation by providing greater flexibility to the electricity system. Due to the relatively low cost of H_2 storage, an addition of H_2 demand was found to lower the system LCOE by 2 €/MWh, to a minimum of 46 €/MWh. Finally, this master's thesis found that increasing the nuclear power investment costs to values higher than 5250 k€/MW, results in the electricity system not having room to accommodate nuclear power generation.

Bibliography

[1] P. A. Owusu and S. Asumadu-Sarkodie, “A review of renewable energy sources, sustainability issues and climate change mitigation”, *Cogent Engineering*, vol. 3, no. 1, p. 1 167 990, 2016.

[2] E. Jonson, C. Azar, K. Lindgren, and L. Lundberg, “Exploring the competition between variable renewable electricity and a carbon-neutral baseload technology”, *Energy Systems*, vol. 11, no. 1, pp. 21–44, 2020.

[3] L. Hirth and I. Ziegenhagen, “Balancing power and variable renewables: Three links”, *Renewable and Sustainable Energy Reviews*, vol. 50, pp. 1035–1051, 2015.

[4] C. P. Castillo, F. B. e Silva, and C. Lavalle, “An assessment of the regional potential for solar power generation in eu-28”, *Energy policy*, vol. 88, pp. 86–99, 2016.

[5] B. Frew, W. Cole, P. Denholm, A. W. Frazier, N. Vincent, and R. Margolis, “Sunny with a chance of curtailment: Operating the us grid with very high levels of solar photovoltaics”, *iScience*, vol. 21, pp. 436–447, 2019.

[6] M. Victoria, K. Zhu, T. Brown, G. B. Andresen, and M. Greiner, “The role of storage technologies throughout the decarbonisation of the sector-coupled european energy system”, *Energy Conversion and Management*, vol. 201, p. 111 977, 2019.

[7] D. P. Schlachtberger, T. Brown, M. Schäfer, S. Schramm, and M. Greiner, “Cost optimal scenarios of a future highly renewable european electricity system: Exploring the influence of weather data, cost parameters and policy constraints”, *Energy*, vol. 163, pp. 100–114, 2018.

[8] D. Atsmon and H. Ek Fälth, “The effect on system cost of decreasing solar and battery costs in regions with different climates”, Master’s thesis, Chalmers University of Technology, Gothenburg, Sweden, 2019.

[9] C. H. Villar, D. Neves, and C. A. Silva, “Solar pv self-consumption: An analysis of influencing indicators in the portuguese context”, *Energy strategy reviews*, vol. 18, pp. 224–234, 2017.

[10] L. Göransson, J. Goop, M. Odenberger, and F. Johnsson, “Impact of thermal plant cycling on the cost-optimal composition of a regional electricity generation system”, *Applied energy*, vol. 197, pp. 230–240, 2017.

[11] V. Johansson, L. Thorson, and L. Göransson, “A quantitative method for evaluation of variation management strategies for integration of renewable electricity generation”, in *16th Wind Integration Workshop*, 2017.

[12] V. Johansson and L. Göransson, "Impacts of variation management on cost-optimal investments in wind power and solar photovoltaics", *Renewable Energy Focus*, vol. 32, pp. 10–22, 2020.

[13] P. Holmér and J. Ullmark, "The potential of heat storage as variation management in the electricity and district heating sectors", Master's thesis, Chalmers University of Technology, Gothenburg, Sweden, 2018.

[14] D. A. Energy, *Technology data*, 2020. [Online]. Available: `https://ens.dk/en/our-services/projections-and-models/technology-data` (visited on 04/29/2020).

[15] N. R. E. Laboratory, *Annual technology baseline, 2018 data*, 2018. [Online]. Available: `http://www.nrel.gov/analysis/data_tech_baseline.html` (visited on 04/29/2020).

[16] L. Hirth, "The market value of variable renewables: The effect of solar wind power variability on their relative price", *Energy economics*, vol. 38, pp. 218–236, 2013.

[17] T. Brown and L. Reichenberg, "Decreasing market value of variable renewables is a result of policy, not variability", *arXiv preprint arXiv:2002.05209*, 2020.

[18] M. Lehtveer, S. Brynolf, and M. Grahn, "What future for electrofuels in transport? analysis of cost competitiveness in global climate mitigation", *Environmental science & technology*, vol. 53, no. 3, pp. 1690–1697, 2019.

[19] L. Göransson and F. Johnsson, "A comparison of variation management strategies for wind power integration in different electricity system contexts", *Wind Energy*, vol. 21, no. 10, pp. 837–854, 2018.

[20] M. Bolhàr-Nordenkampf, *Economic assessment of biomass gasification compared to other renewable technologies.* na, 2006.

[21] H. Thunman, A. Larsson, and M. Hedenskog, "Commissioning of the gobigas 20mw bio-methane plant", *tcbiomass2015*, 2015.

[22] F. Lvque, *The economics and uncertainties of nuclear power.* Cambridge University Press, 2015.

[23] F. Ueckerdt, R. Brecha, and G. Luderer, "Analyzing major challenges of wind and solar variability in power systems", *Renewable energy*, vol. 81, pp. 1–10, 2015.

[24] D. Schlachtberger, S. Becker, S. Schramm, and M. Greiner, "Backup flexibility classes in emerging large-scale renewable electricity systems", *Energy Conversion and Management*, vol. 125, pp. 336–346, 2016.

[25] P. Eser, A. Singh, N. Chokani, and R. S. Abhari, "Effect of increased renewables generation on operation of thermal power plants", *Applied Energy*, vol. 164, pp. 723–732, 2016.

[26] R. Turconi, C. O'Dwyer, D. Flynn, and T. Astrup, "Emissions from cycling of thermal power plants in electricity systems with high penetration of wind power: Life cycle assessment for ireland", *Applied energy*, vol. 131, pp. 1–8, 2014.

[27] S. Budinis, S. Krevor, N. Mac Dowell, N. Brandon, and A. Hawkes, "An assessment of ccs costs, barriers and potential", *Energy strategy reviews*, vol. 22, pp. 61–81, 2018.

[28] D. A. Halamay, T. K. Brekken, A. Simmons, and S. McArthur, “Reserve requirement impacts of large-scale integration of wind, solar, and ocean wave power generation”, *IEEE Transactions on Sustainable Energy*, vol. 2, no. 3, pp. 321–328, 2011.

[29] F. J. De Sisternes, J. D. Jenkins, and A. Botterud, “The value of energy storage in decarbonizing the electricity sector”, *Applied Energy*, vol. 175, pp. 368–379, 2016.

[30] M. Steurer, U. Fahl, A. Voß, and P. Deane, “Curtailment: An option for cost-efficient integration of variable renewable generation?”, in *Europe’s Energy Transition-Insights for Policy Making*, Elsevier, 2017, pp. 97–104.

[31] A. Grübler, *Technology and global change*. Cambridge university press, 2003.

[32] A. McDonald and L. Schrattenholzer, “Learning curves and technology assessment”, *International Journal of Technology Management*, vol. 23, no. 7/8, pp. 718–745, 2002.

[33] M. Shahmarichatghieh, A. Tolonen, H. Haapasalo, *et al.*, “Product life cycle, technology life cycle and market life cycle; similarities, differences and applications”, in *Technology, Innovation and Industrial Management Joint International Conference*, 2015.

[34] E. S. Rubin, I. M. Azevedo, P. Jaramillo, and S. Yeh, “A review of learning rates for electricity supply technologies”, *Energy Policy*, vol. 86, pp. 198–218, 2015.

[35] I. R. E. A. (IRENA), *Renewable capacity statistics 2020*, 2020. [Online]. Available: `https://www.irena.org/Statistics` (visited on 04/23/2020).

[36] S. C. Bhattacharyya and G. R. Timilsina, “A review of energy system models”, *International Journal of Energy Sector Management*, 2010.

[37] J. R. McFarland, J. M. Reilly, and H. J. Herzog, “Representing energy technologies in top-down economic models using bottom-up information”, *Energy Economics*, vol. 26, no. 4, pp. 685–707, 2004.

[38] H. Lund, F. Arler, P. A. Østergaard, F. Hvelplund, D. Connolly, B. V. Mathiesen, and P. Karnøe, “Simulation versus optimisation: Theoretical positions in energy system modelling”, *Energies*, vol. 10, no. 7, p. 840, 2017.

[39] U. N. F. C. on Climate Change, “Adoption of the paris agreement. report no. fccc/cp/2015/l. 9/rev. 1”, 2015.

[40] J. Rogelj, M. Den Elzen, N. Höhne, T. Fransen, H. Fekete, H. Winkler, R. Schaeffer, F. Sha, K. Riahi, and M. Meinshausen, “Paris agreement climate proposals need a boost to keep warming well below 2°c”, *Nature*, vol. 534, no. 7609, pp. 631–639, 2016.

[41] I. Intergovernmental Panel on Climate Change, “Special report: Global warming of 1.5°c”, 2018.

[42] G. Papaefthymiou and K. Dragoon, “Towards 100% renewable energy systems: Uncapping power system flexibility”, *Energy Policy*, vol. 92, pp. 69–82, 2016.

[43] A. P. do Ambiente, “Roadmap for carbon neutrality 2050 (rnc2050) - long-term strategy for carbon neutrality of the portuguese economy by 2050”, 2019.

[44] A. Zerrahn, W.-P. Schill, and C. Kemfert, “On the economics of electrical storage for variable renewable energy sources”, *European Economic Review*, vol. 108, pp. 259–279, 2018.

[45] H. Zhang, J. Baeyens, J. Degrève, and G. Cacères, “Concentrated solar power plants: Review and design methodology”, *Renewable and sustainable energy reviews*, vol. 22, pp. 466–481, 2013.

[46] K. Hedegaard and P. Meibom, “Wind power impacts and electricity storage–a time scale perspective”, *Renewable Energy*, vol. 37, no. 1, pp. 318–324, 2012.

[47] N. Stern, “A story of growth”, *ACADEMIA-The magazine of the Polish Academy of Sciences*, pp. 16–21, 2019.

[48] J. Khan and M. H. Arsalan, “Solar power technologies for sustainable electricity generation–a review”, *Renewable and Sustainable Energy Reviews*, vol. 55, pp. 414–425, 2016.

[49] Enerdata, *World energy consumption*, 2018. [Online]. Available: `https://yearbook.enerdata.net/total-energy/world-consumption-statistics.html` (visited on 04/25/2020).

[50] P. Ralon, M. Taylor, A. Ilas, H. Diaz-Bone, and K. Kairies, “Electricity storage and renewables: Costs and markets to 2030”, *International Renewable Energy Agency: Abu Dhabi, United Arab Emirates*, 2017.

[51] H. Rubel, C. Pieper, J. Zenneck, and Y. Sunak, “How batteries and solar power are disrupting electricity markets”, *The Boston Consulting Group, 2015*, 2017.

[52] D. Chattopadhyay, N. Frydas, T. Kramskaya, and E. Tavoulareas, “Battery storage in developing countries: Key issues to consider”, *The Electricity Journal*, vol. 32, no. 2, pp. 1–6, 2019.

[53] L. Goldie-Scot, “A behind the scenes take on lithium-ion battery prices”, *Bloomberg New Energy Finance*, 2019.

[54] J. Arteaga and H. Zareipour, “A price-maker/price-taker model for the operation of battery storage systems in electricity markets”, *IEEE Transactions on Smart Grid*, vol. 10, no. 6, pp. 6912–6920, 2019.

[55] W. Cole, B. Frew, P. Gagnon, A. Reimers, J. Zuboy, and R. Margolis, “Envisioning a low-cost solar future: Exploring the potential impact of achieving the sunshot 2030 targets for photovoltaics”, *Energy*, vol. 155, pp. 690–704, 2018.

[56] A. Saltelli, S. Tarantola, F. Campolongo, and M. Ratto, *Sensitivity analysis in practice: a guide to assessing scientific models.* Wiley Online Library, 2004, vol. 1.

[57] ETNOSE-E, *Hourly load values for a specific country for a specific month*, 2015. [Online]. Available: `https://www.entsoe.eu/db-query/consumption/mhlv-a-specific-country-for-a-specific-month` (visited on 04/29/2020).

[58] V. Johansson, L. Thorson, J. Goop, L. Göransson, M. Odenberger, L. Reichenberg, M. Taljegard, and F. Johnsson, “Value of wind power–implications from specific power”, *Energy*, vol. 126, pp. 352–360, 2017.

[59] M. M. Rienecker, M. J. Suarez, R. Gelaro, R. Todling, J. Bacmeister, E. Liu, M. G. Bosilovich, S. D. Schubert, L. Takacs, G.-K. Kim, *et al.*, “Merra: Nasa’s modern-era retrospective analysis for research and applications”, *Journal of climate*, vol. 24, no. 14, pp. 3624–3648, 2011.

[60] D. P. Dee, S. M. Uppala, A. Simmons, P. Berrisford, P. Poli, S. Kobayashi, U. Andrae, M. Balmaseda, G. Balsamo, d. P. Bauer, *et al.*, “The era-interim reanalysis: Configuration and performance of the data assimilation system”,

Quarterly Journal of the royal meteorological society, vol. 137, no. 656, pp. 553–597, 2011.

[61] J. Olauson and M. Bergkvist, "Modelling the swedish wind power production using merra reanalysis data", *Renewable Energy*, vol. 76, pp. 717–725, 2015.

[62] K. Nilsson and T. Unger, "Bedömning av en europeisk vindkraftpotential med gis-analys", *Project Report*, 2014.

[63] Z. Norwood, E. Nyholm, T. Otanicar, and F. Johnsson, "A geospatial comparison of distributed solar heat and power in europe and the us", *PloS one*, vol. 9, no. 12, e112442, 2014.

A

Appendix

A.1 Levelized Cost of Electricity

A.1.1 System LCOE

System LCOE is defined as the total system cost dividing by the total demand.

$$\textbf{System LCOE} = \frac{SystemTotalCost}{TotalDemand}, [€/MWh] \tag{A.1}$$

A.1.2 Technology LCOE

Technology LCOE is defined as being the cost of producing one unit of electricity. Thus, technology LCOE, which strongly depends on different cost, is set as:

$$\textbf{Technology LCOE} = \frac{C_{\text{inv}} \times A}{t \times capacityfactor} + OM_{\text{v}} + \frac{OM_{\text{f}}}{t} + \frac{C_{\text{fuel}}}{\eta}, [€/MWh] \tag{A.2}$$

A.2 Model

A list of the sets, variables, and parameters implemented in the model used in this master's thesis. Important to note, that this list only considers the range of factors more relevant to this very master's thesis. Nevertheless, as previous mentioned, it is possible to find a detailed mathematical description of the model in [12].

Table A.1: Sets (upper-case), parameters (italic upper-case), and variables (italic lower-case) implemented in the model used in this master's thesis.

Sets

P	Electricity Generation Technologies[1]
H_2	Hydrogen Production Technology[2]
T	Timesteps

Parameters

C_{inv}	Investment Cost of a Technology [€/kW]
C_{fuel}	Fuel Cost [€/MWh]
C_{CCS}	CCS Technologies Cost [€/MWh]
D^{el}	Electricity Demand [MWh/h]
D^{H_2}	Hydrogen Demand [MWh/h]
η	Efficiency
OM_f	Fixed Operation and Maintenance Cost [€/kW]
OM_v	Variable Operation and Maintenance Cost [€/MWh]
E_{cap}	Cap of CO_2 Emissions [$GtCO_2$]
E	CO_2 Emission [$GtCO_2$]
A	Annuity Factor

Variables

g	Electricity Generated [MWh/h]
x_{elec}	Hydrogen Generated [MWh/h]
i	Investment [kW]
soc_{H_2}	State of Charge - Hydrogen Strorage [MWh/h]
c_{cycl}	Cycling Cost [€]
c_{tot}	Total System Cost (objective value) [€/year]

[1] Combination of dispatch energy sources and VRESs. VRESs are composed of 12 different types of wind onshore power, wind offshore, and solar PV.
[2] Electrolysers

A.3 Input Data

The pre-existing input data in the model which was used in this master's thesis. The data accounts for fuel properties, as well as economical and technical data for different technologies.

Table A.2: Pre-existing fuels properties in the model.

Fuel	Carbon Intensity [kg/MWh]
Hard Coal (H)	25.93
Natural Gas (G)	15.68
Biomass (W)	30.68[1]
Nuclear (U)	0
Biogas (WG)	15.68[1]

[1] Biomass and biogas, as biofuel technologies are carbon-neutral. Still the carbon intensity is required to calculate the negative emissions for the biomass when used in combination with CCS technologies.

Table A.3: Pre-existing VRES economic and technical properties in the model.

	Lifespan [yr]	OM_var [€/MWh]	OM_fix [€/kW/yr]	FLH [hr/yr]
Wind Onshore[1]	30	1.1	12.6	3259
Wind Offshore	30	1.1	36.0	4196
Solar PV	40	1.1	6.5	1732

[1] Only wind onshore 200 W/m^2.

Table A.4: Pre-existing H_2 and battery devices economic and technical properties in the model.

	Lifespan [yr]	OM_var [€/MWh]	OM_fix [€/kW/yr]	η[%]
H_2 Fuel Cell	10	3.0	55.0	50[1]
H_2 Electrolyzer	20	0	18.0	79[2]
Battery Energy	25	0	20.0	92[2]
Battery Power	25	0	0.54	100[1]

[1] Efficiency of discharge.
[2] Efficiency of charge.

Table A.5: Pre-existing fuel economic and technical properties in the model.

	Lifespan [yr]	Inv. cost [€/MWh]	OM_var [€/MWh]	OM_fix [€/kW/yr]	η[%]	Start Time [h]	Min Load	Start Cost [k€]	Start Fuel [MWh]	Start Fuel Type	Part Load Cost [€/MW]
Coal Power	40	2049	2.1	44.9	56	12	0.35	56.9	2.93	Oil	1.9
Natural Gas	30	932	0.8	17.3	71	6	0.20	42.9	0.05	Natural Gas	0.5
Natural Gas Peak	30	466	0.4	15.6	42	0	0.50	20.2	0.45		0.5
Biogas	30	932	0.8	13.0	71	6	0.20	42.9	0.05	Biomass	0.5
Biogas Peak	30	466	0.7	7.9	42	0	0.50	20.2	0.45		0.5
Biomass Power	40	2049	2.1	54.1	50	12	0.35	56.9	2.93		1.9
Nuclear Power	60	4124	0	153.7	43	24	0.70	400	0	Nuclear	1

Table A.6: Pre-existing fuel with CCS technology plants economic and technical properties in the model.

	Lifespan [yr]	Inv. Cost [€/MWh]	OM_var [€/MWh]	OM_fix [€/kW/yr]	η[%]	Start Time [h]	Min Load	Start Cost [k€]	Start Fuel [MWh]	Start Fuel Type	Part Load Cost [€/MW]	Carbon Share
BECCS	40	3314	2.1	130.2	34	12	0.35	56.9	2.93	Biomass	1.9	85
HWCCS	40	3054	1.8	92.5	41	12	0.35	56.9	2.93		1.9	88
WGCCS	30	1626	2.1	40.2	53	12	0.35	56.9	2.93		1.9	89
GWGCCS	30	1626	2.1	40.2	53	12	0.35	56.9	2.93		1.9	89

A.4 Results

This section presents additional data obtained in this study. It is given the impact of different technologies investment and fuel cost on the solar PV share. Also for each scenario, two tables reflect the cost of different technologies associated with a specific solar power investment cost. Finally, it is shown the annual generation for each of the three cases studied in the base scenario: high solar share; high nuclear share; and high VRESs share.

A.4.1 Probability Plot

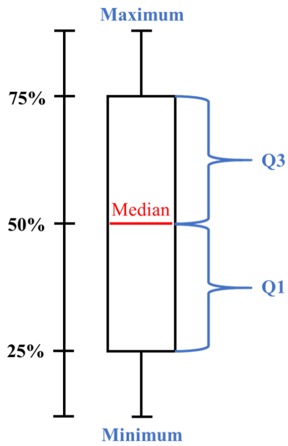

Figure A.1: Box plot interpretation.

Minimum value is the least value.

Q1 is the lower quartile. Hence, higher values than Q1 have 75% probability to occur, while lower values are associated to 25% probability to occur.

Median is the middle value, and thus both higher and lower values than median have 50% probability to occur.

Q3 is the higher quartile. Hence, higher values than Q3 have 25% probability to occur, while lower values are associated to 75% probability to occur.

Maximum value is the highest value.

A.4.2 Base Scenario

Note that in this section the results for the expensive battery scenario are also included - high battery storage investment cost.

A.4.2.1 Impact of Different Technologies' Investment and Fuel Cost

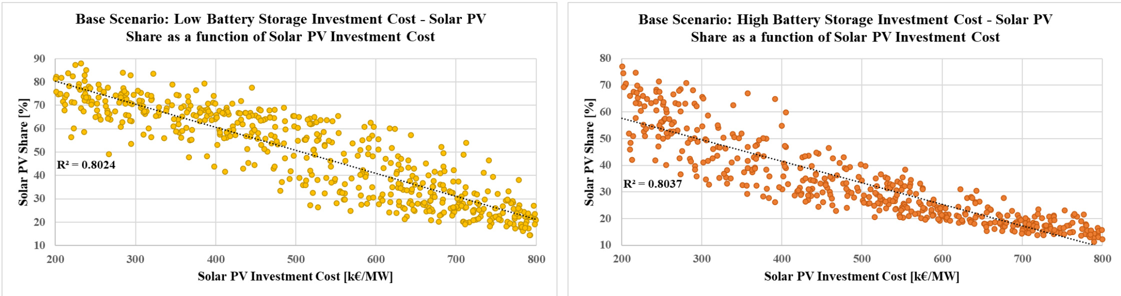

Figure A.2: Impact of solar PV investment cost on the solar PV share in the base scenario for low and high battery storage investment cost.

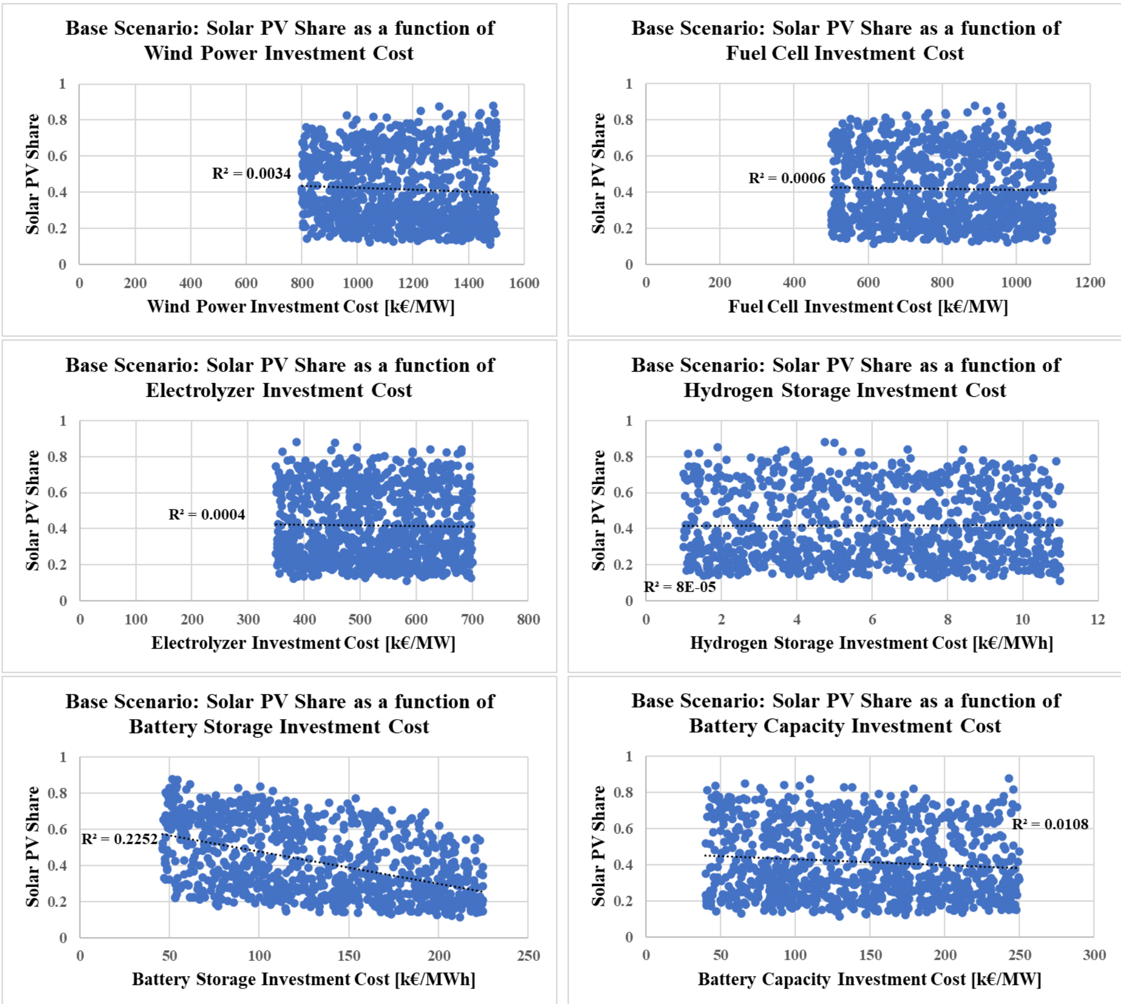

Figure A.3: Impact of the different technologies' investment cost on the solar PV share in the base scenario.

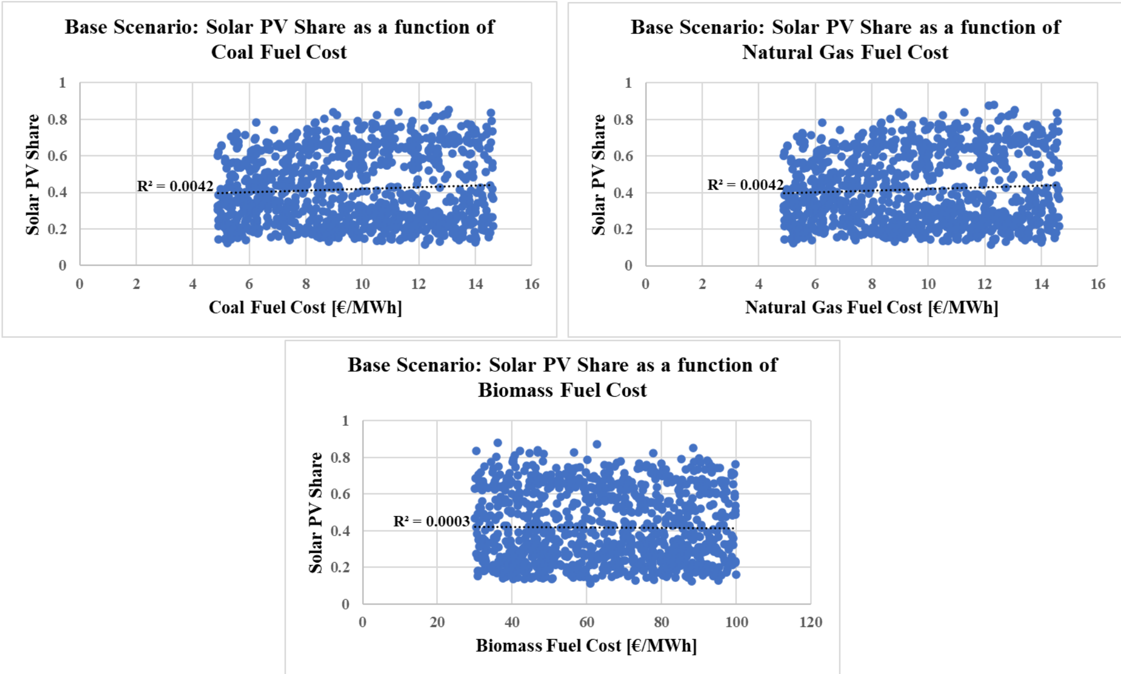

Figure A.4: Impact of the different technologies' fuel cost on the solar PV for the base scenario.

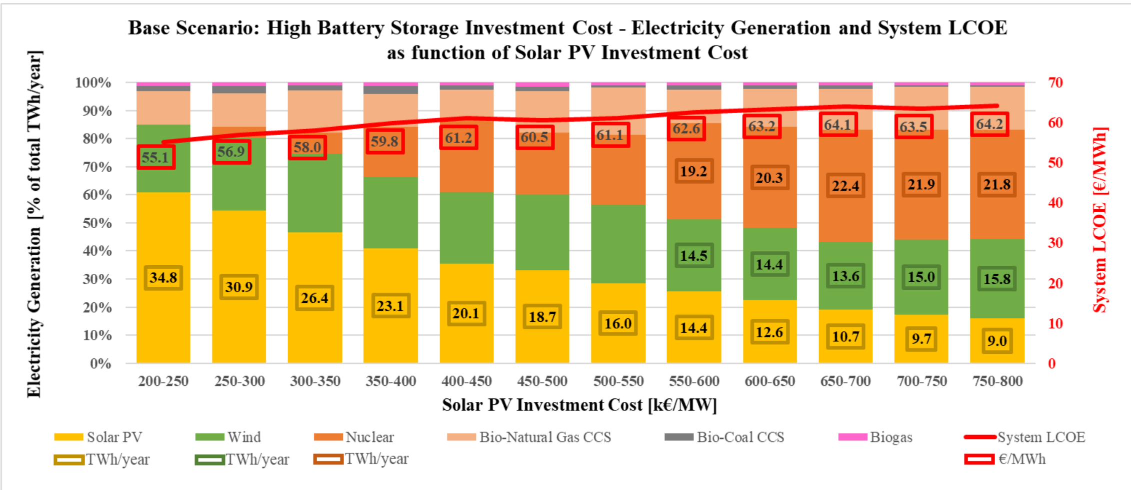

Figure A.5: Base scenario: Generation mix and system LCOE at high battery storage investment cost. Only data labels for technologies with higher share than solar power are included.

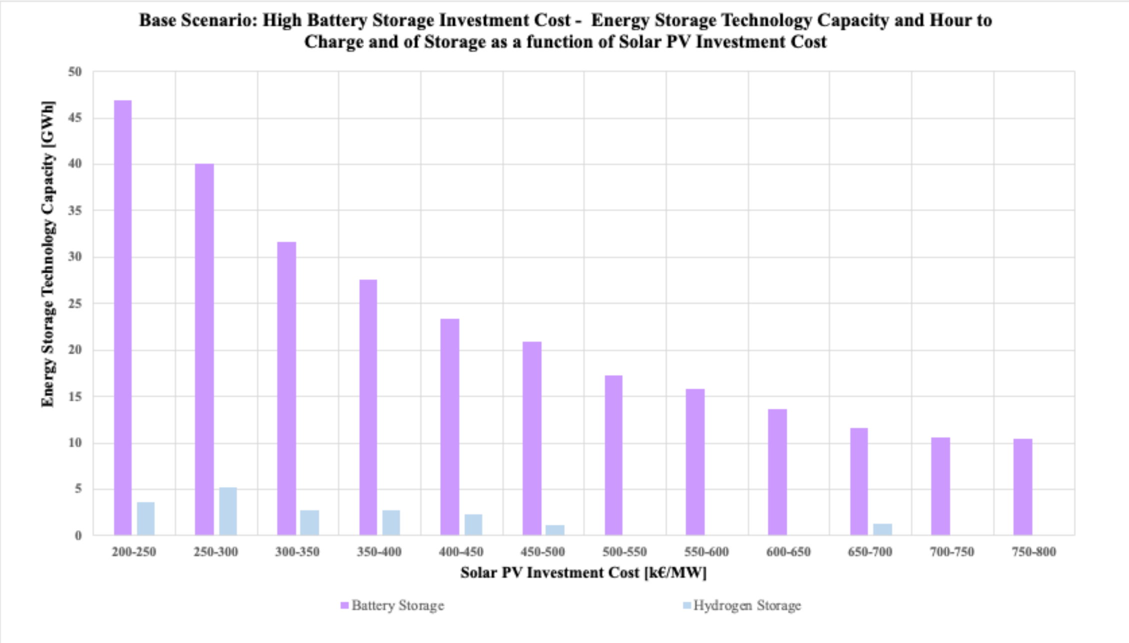

Figure A.6: Base scenario: Energy storage technology capacity and time required to charge and discharge a battery at high battery storage investment cost.

Table A.7: Investment cost of different technologies for different solar power investment costs for the base scenario. L corresponds to low battery investment cost case and H corresponds to high battery investment cost case.

	Solar Power Investment Cost [k€/MW]	**200-250**	**250-300**	**300-350**	**350-400**	**400-450**	**450-500**	**500-550**	**550-600**	**600-650**	**650-700**	**700-750**	**750-800**
Wind Power [k€/MW]	**L**	1101.25	1153.57	1202.61	1141.3	1122.53	1176.58	1162.82	1202.27	1189.94	1186.86	1167.2	1123.74
	H	1126.25	1118.46	1146.29	1153.01	1190.38	1144.91	1144.19	1135.15	1179.11	1228.47	1165.27	1151.55
Battery Storage [k€/MWh]	**L**	85.51	93.87	98.54	90.93	85.9	90.29	90.4	91.14	91.59	91.03	87.54	92.71
	H	180.48	180.65	187.8	187.36	177.83	173.23	177.46	180.7	181.17	187.17	186.78	176.6
Battery Capacity [k€/MW]	**L**	148.7	135.73	143.94	135.98	139	138.48	154.33	149.95	147.38	137.45	132.57	135.15
	H	135.93	146.51	138.84	149.02	148.4	146.59	160.41	144.52	136.56	164.38	143.83	146.38
H_2 Storage [k€/MWh]	**L**	6.32	5.63	6.31	5.74	6.19	5.9	6.57	6.68	5.68	5.64	6.15	5.69
	H	6.61	6.29	6.41	6.27	5.33	6.09	6.27	6.01	5.99	6.01	5.57	6.26
Fuel Cell [k€/MW]	**L**	717.88	808.33	782.36	802.8	763.41	825.62	769.98	795.12	839.52	799.79	822.8	816.33
	H	798.89	823.12	837.78	813.48	796.1	781.79	795.66	776.84	806.21	800.43	800.44	775.23
Electrolyzer [k€/MW]	**L**	540.63	518.18	520.77	516.97	533.61	525.67	533.75	535.59	518.39	523.47	517.99	508.99
	H	509.09	517.27	529.58	549.39	537.21	517.29	520.33	514.17	510.17	535.88	547.72	550.2

Table A.8: Fuel cost for different solar power investment cost for the base scenario. L corresponds to low battery investment cost case and H corresponds to high battery investment cost case.

	Solar Power Investment Cost [k€/MW]	**200-250**	**250-300**	**300-350**	**350-400**	**400-450**	**450-500**	**500-550**	**550-600**	**600-650**	**650-700**	**700-750**	**750-800**
Nuclear [€/MWh]		6	6	6	6	6	6	6	6	6	6	6	6
Coal [€/MWh]	**L**	9.31	10.02	10.73	9.75	9.86	9.36	9.89	9.97	9.44	9.44	9.86	9.36
	H	9.79	9.88	10.02	9.85	10.35	9.29	9.12	10.34	9.76	9.75	8.59	9.57
Natural Gas [€/MWh]	**L**	32.67	35.14	37.62	34.2	34.58	32.83	34.7	34.97	33.1	33.11	34.59	32.85
	H	34.34	34.66	35.14	34.56	36.31	32.58	31.99	36.29	34.23	34.21	30.13	33.56
Biomass [€/MWh]	**L**	60.66	64.85	60.44	65.16	62.39	62.85	67.54	66.59	63.93	62.37	65.52	63.42
	H	63.98	66.51	64.72	68.46	60.48	68.47	63.27	66.53	61.46	63.84	58.29	64.71
Biogas [€/MWh]	**L**	106.66	112.64	106.34	113.08	109.13	109.79	116.49	115.13	111.33	109.11	113.6	110.6
	H	111.41	115.01	112.46	117.81	106.4	117.81	110.39	115.05	107.8	111.2	103.28	112.44

A.4.2.2 Special Cases

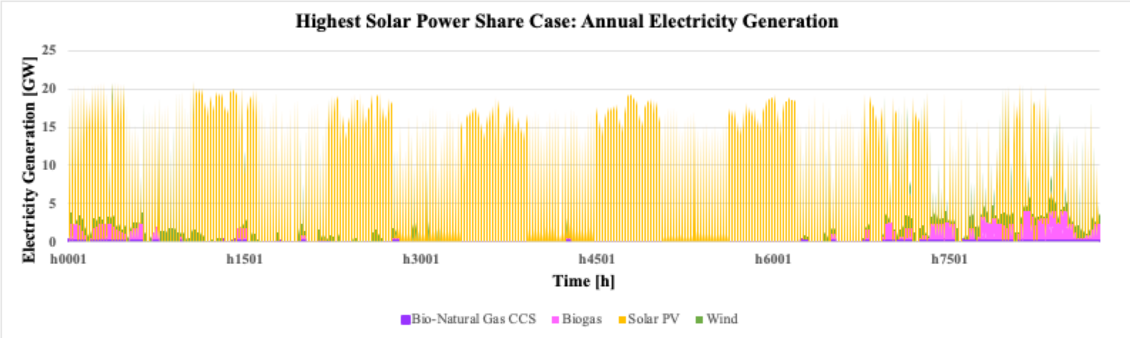

Figure A.7: Annual electricity generation in the highest solar power share case.

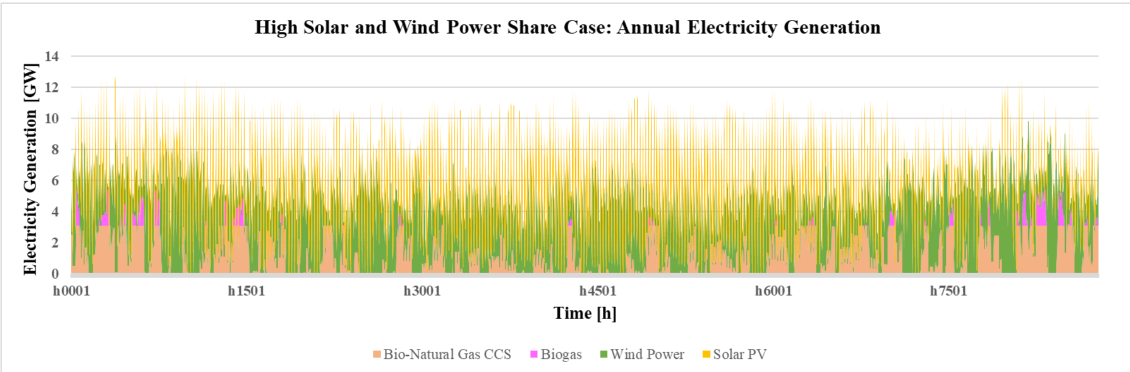

Figure A.8: Annual electricity generation in the high solar and wind share case.

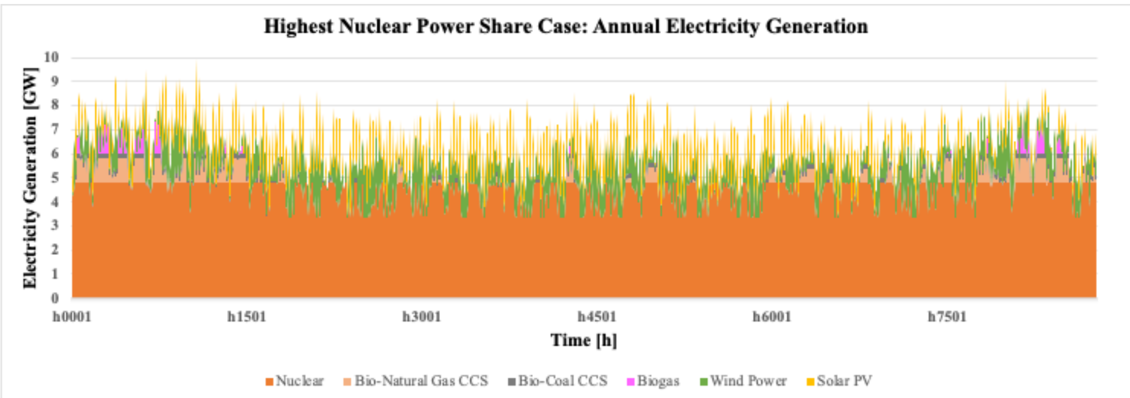

Figure A.9: Annual electricity generation in the highest nuclear power share case.

Table A.9: Input data - technologies' investment cost - of the different cases studied in the base scenario.

Case			Highest Solar Power	High Solar and Wind Power	Highest Nuclear Power
Investment Cost	**Solar PV**	**k€/MW**	232.05	480.48	765.05
	Wind Onshore		1489.19	806.20	806.91
	Wind Offshore		1826.52	1634.50	1830.33
	Battery Capacity		242.97	81.09	211.70
	Electrolyzer		386.68	409.51	625.70
	Fuel Cell		888.70	693.38	959.30
	Battery Storage	**k€/MWh**	51.57	203.13	959.30
	H_2 Storage		4.75	2.54	3.54

Table A.10: Input data - fuel cost - of the different cases studied in the base scenario.

Case			Highest Solar Power	High Solar and Wind Power	Highest Nuclear Power
Fuel Cost	**Hard Coal**	**€/MWh**	12.33	8.58	7.09
	Natural Gas		43.24	30.12	24.89
	Biomass		36.21	44.50	37.25
	Biogas		71.71	83.56	73.22
	Nuclear		6		

A.4.3 No CCS Technology Scenario

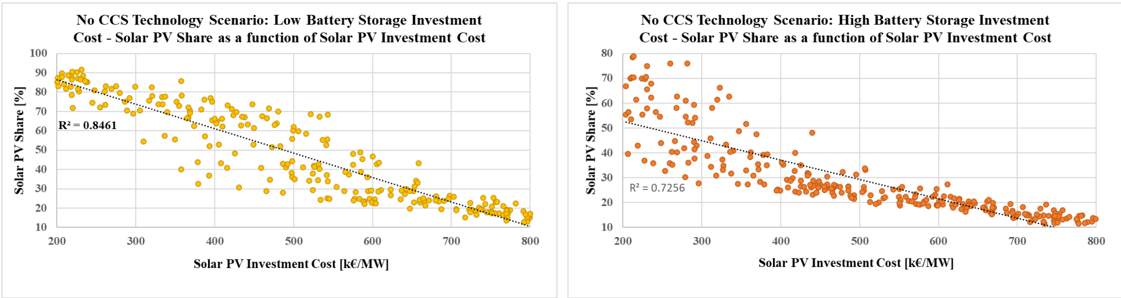

Figure A.10: No CCS Scenario: Impact of solar PV investment cost on the solar PV share for the low and high battery storage investment cost case.

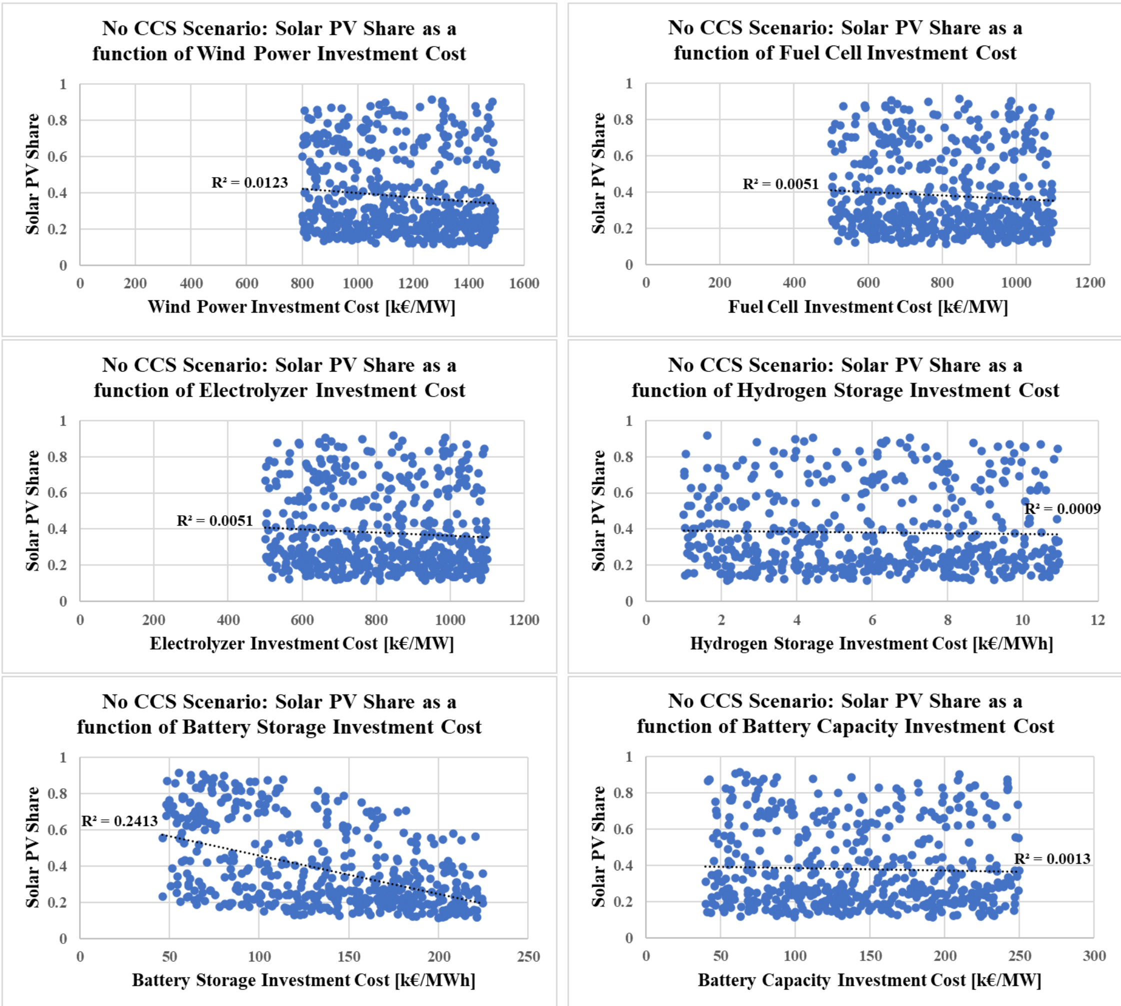

Figure A.11: Impact of the different technologies' investment cost on the solar PV share in the no CCS technology scenario.

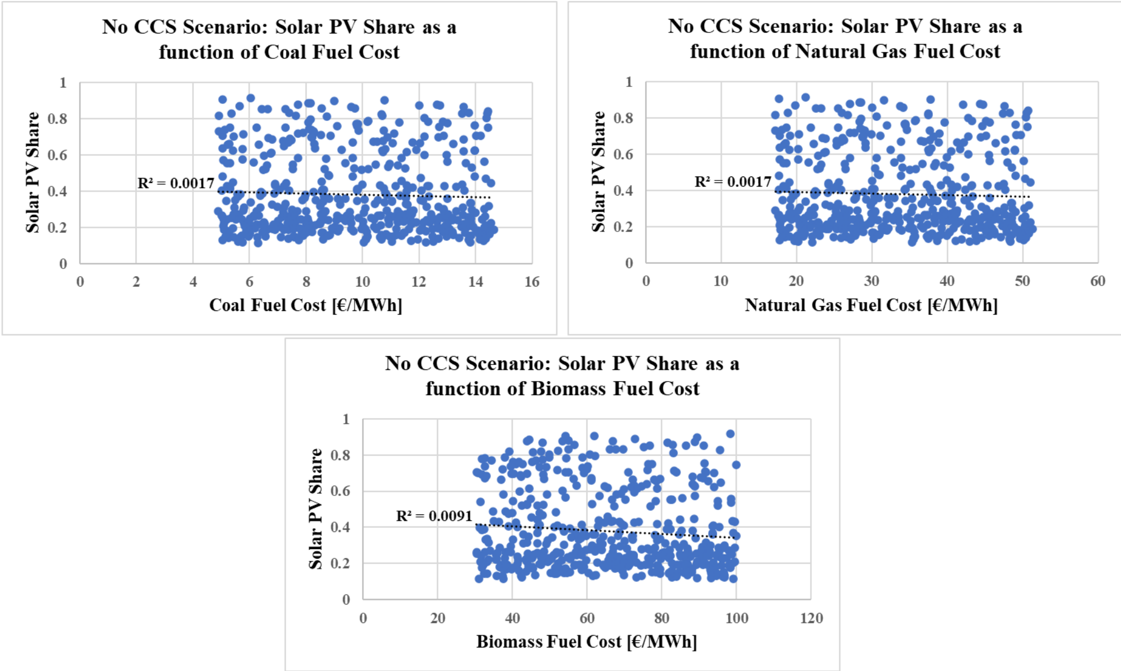

Figure A.12: Impact of the different technologies' fuel cost on the solar PV for the no CCS technology scenario.

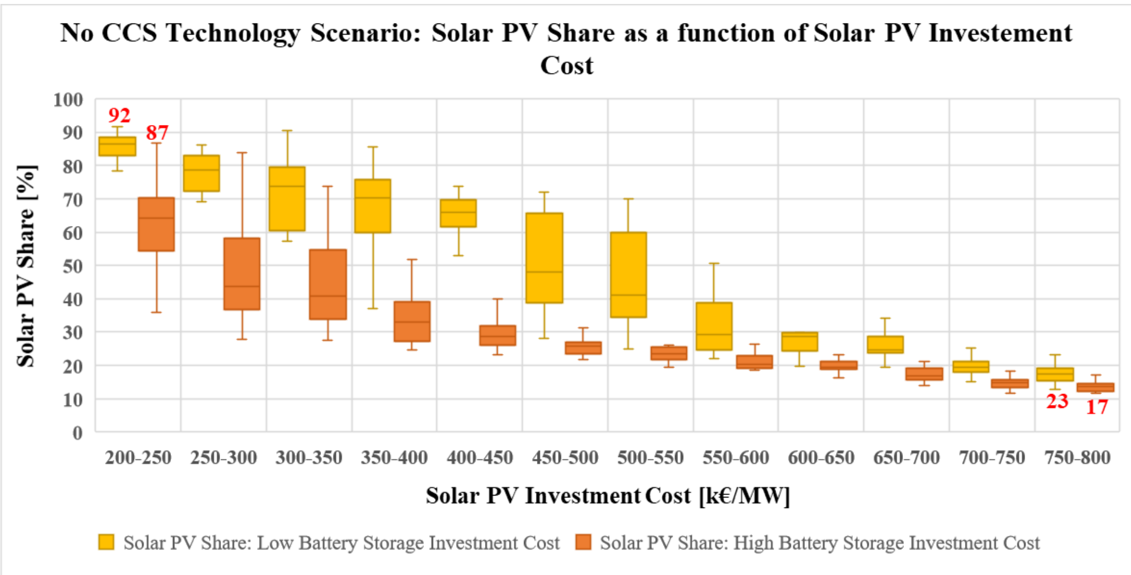

Figure A.13: No CCS Scenario: Probability of solar PV share according to different solar power investment costs for both low and high battery storage investment cost cases.

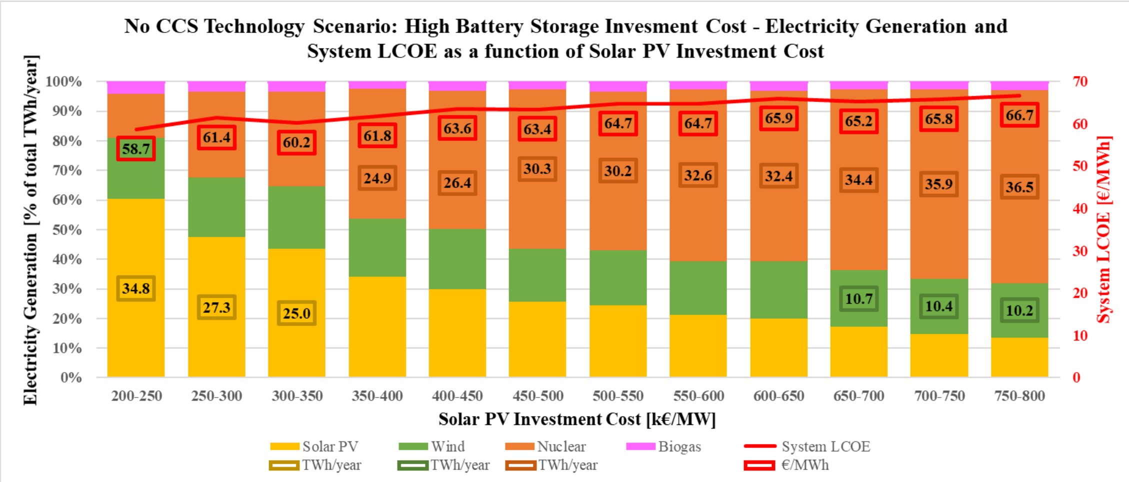

Figure A.14: No CCS Scenario: Generation mix and system LCOE at high battery storage investment cost. Only data labels for technologies with higher share than solar power are included.

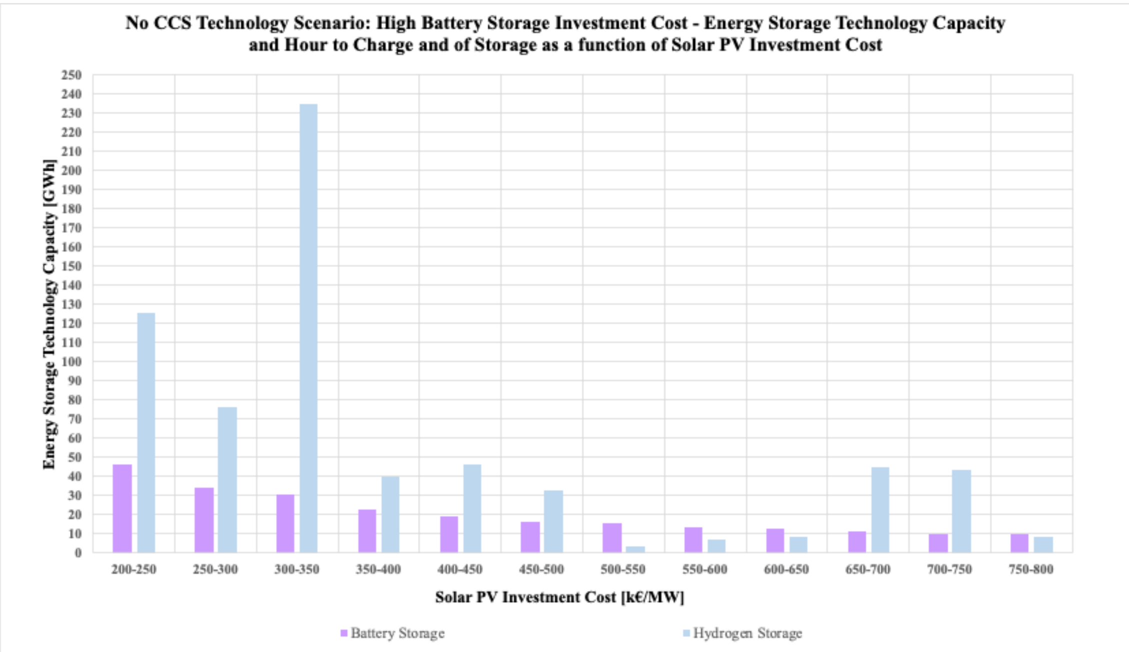

Figure A.15: No CCS Scenario: Energy storage technology capacity and time required to charge and discharge a battery at high battery storage investment cost.

Table A.11: Investment cost of different technologies for different solar power investment costs for the no CCS technology scenario. L corresponds to low battery investment cost case and H corresponds to high battery investment cost case.

	Solar Power Investment Cost [k€/MW]	**200-250**	**250-300**	**300-350**	**350-400**	**400-450**	**450-500**	**500-550**	**550-600**	**600-650**	**650-700**	**700-750**	**750-800**
Wind Power [k€/MW]	**L**	1152.74	1009.9	1315.56	1129.61	1109.3	1195.61	1202.47	1101.19	1169	1129.89	1233.47	1141.98
	H	1086.66	1162.06	1183.27	1135.8	1115.21	1198.27	1207.93	1147.51	1134.64	1120.16	1176.73	1191.68
Battery Storage [k€/MW]	**L**	86.99	97.98	95.18	83.17	80.04	83.04	86.09	98.8	88.96	89.76	98.32	98.1
	H	177.66	179.78	169	177.98	181.92	176.72	172.88	180.37	172.14	184.96	183.3	177.85
Battery Capacity [k€/MW]	**L**	145.82	142.24	140.23	145.25	152.18	139.49	133.09	145.71	132.14	126.54	150.09	128.36
	H	149.5	133.53	153.11	148.99	132.03	139.76	174.96	144.69	125.67	130.69	142.96	142.36
H_2 Storage [k€/MW]	**L**	6.89	5.77	5.85	6.07	6.34	5.61	5.58	5.98	5.78	6.49	7.04	6.79
	H	5.94	5.36	5.93	5.53	5.68	6.74	6.25	6.55	6.06	5.57	6.41	6.08
Fuel Cell [k€/MW]	**L**	789.78	885.01	729.64	790.57	812.26	852.38	812	775.67	844	838.08	852.97	811.71
	H	797.19	819.52	738.94	713.24	829.01	788.28	844.12	870.45	788.63	853.33	831.62	854.53
Electrolyzer [k€/MW]	**L**	533.68	524.17	552.8	515.66	519.38	520.4	541.35	551.55	544.46	538.36	572.15	490.98
	H	535.8	512.87	503.64	478.7	507.58	476.34	564.95	540.73	556.74	525.41	532.56	509.88

Table A.12: Fuel cost for different solar power investment costs for the no CCS technology scenario. L corresponds to low battery investment cost case and H corresponds to high battery investment cost case.

	Solar Power Investment Cost [k€/MW]	**200-250**	**250-300**	**300-350**	**350-400**	**400-450**	**450-500**	**500-550**	**550-600**	**600-650**	**650-700**	**700-750**	**750-800**
Nuclear [€/MWh]		6	6	6	6	6	6	6	6	6	6	6	6
Coal [€/MWh]	**L**	9.3	9.82	10.2	9.37	8.83	9.19	9.88	8.76	10.12	9.37	9.25	9.15
	H	9.19	10.16	8.89	10.33	9.46	9.4	10.15	10.01	10.02	9.86	9.63	10.63
Natural Gas [€/MWh]	**L**	32.62	34.45	35.78	32.87	30.96	32.23	34.66	30.72	35.49	32.87	32.46	32.09
	H	32.24	35.64	31.19	36.24	33.17	32.98	35.62	35.1	35.16	34.59	33.78	37.28
Biomass [€/MWh]	**L**	68.1	55.27	59.33	69.52	70.15	67.31	61.05	65.66	62.17	62.27	62.9	70.14
	H	62.89	65.47	62.75	74.33	66.41	66.79	60.62	67.96	59.27	65.07	66.52	60.26
Biogas [€/MWh]	**L**	117.29	98.96	104.76	119.32	120.21	116.16	107.22	113.8	108.82	108.96	109.86	120.2
	H	109.84	113.53	109.65	126.18	114.88	115.42	106.6	117.09	104.68	112.95	115.03	106.09

A.4.4 Industrial Demand Scenario

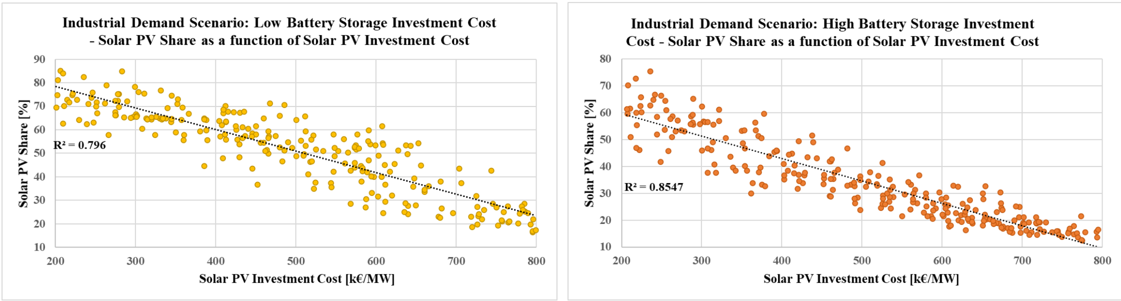

Figure A.16: Industrial Demand Scenario: Impact of solar PV investment cost on the solar PV share for the low and high battery storage investment cost case.

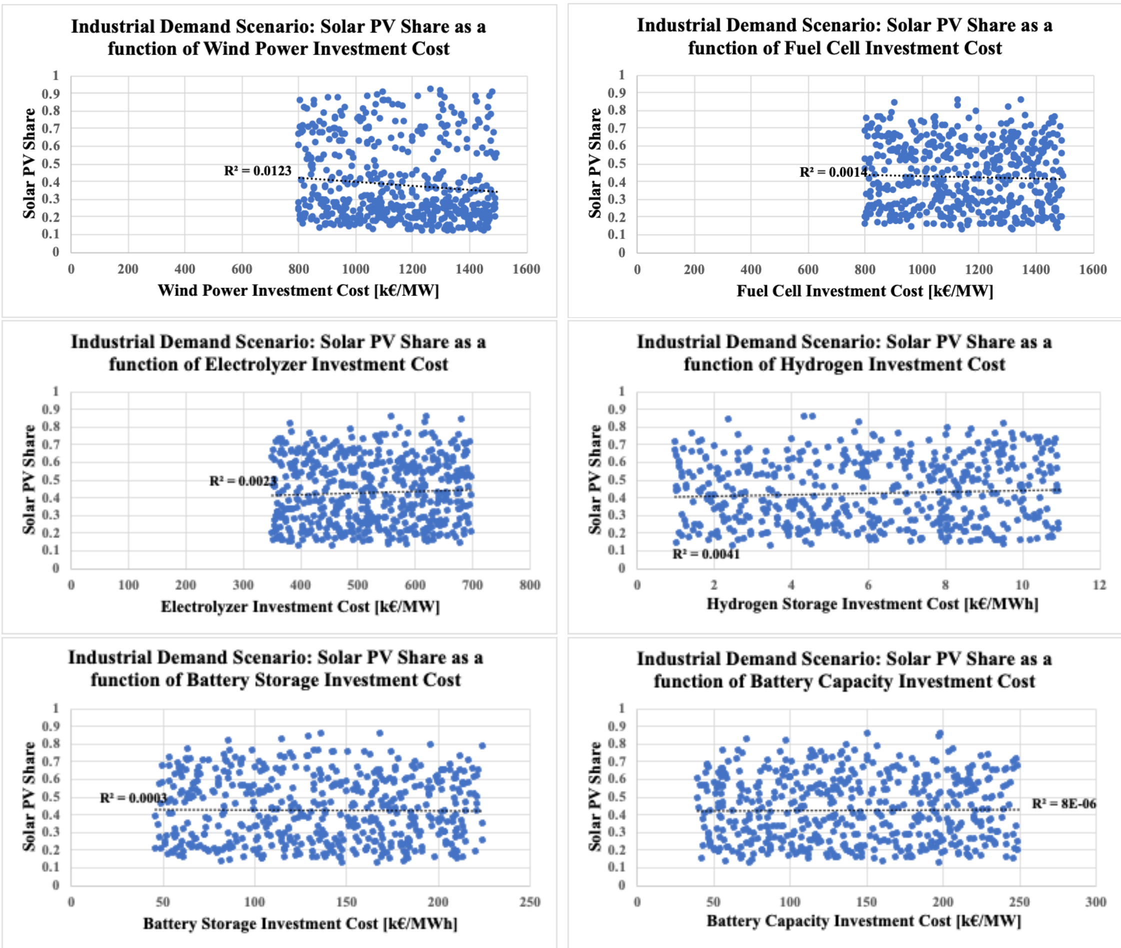

Figure A.17: Impact of the different technologies' investment cost on the solar PV share in the industrial demand scenario.

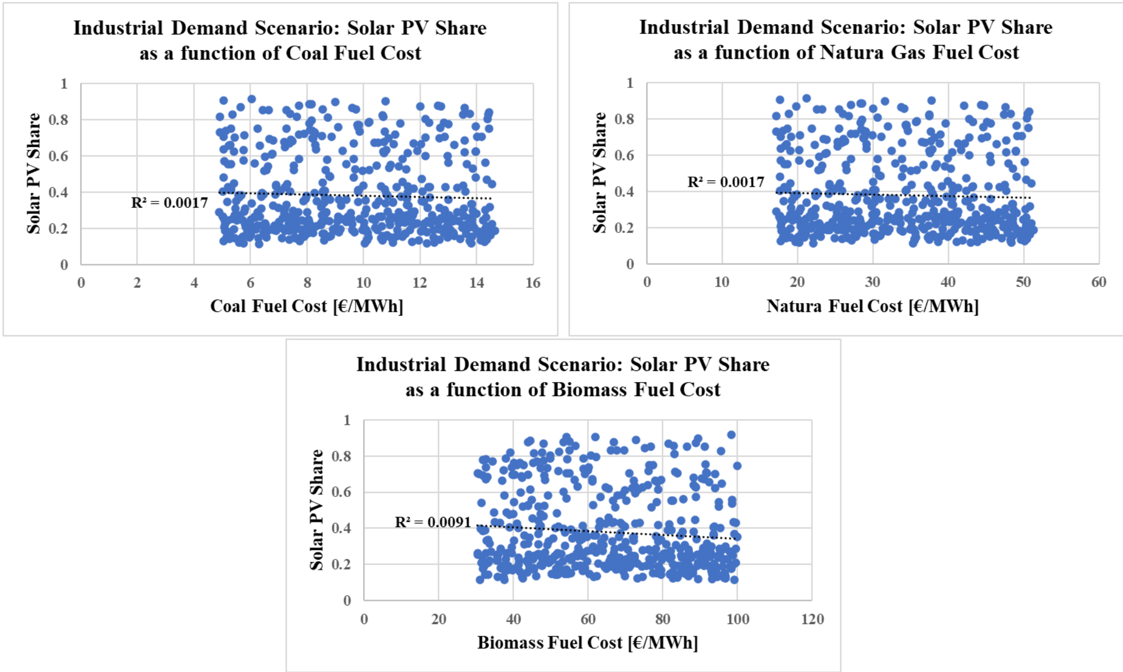

Figure A.18: Impact of the different technologies' fuel cost on the solar PV for the industrial demand scenario.

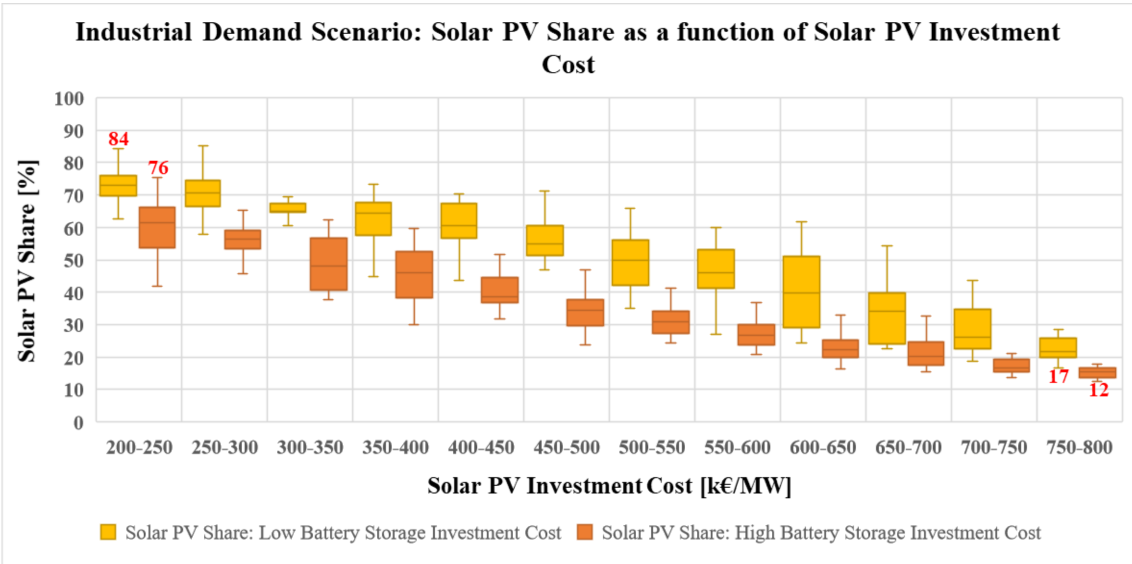

Figure A.19: Industrial Demand Scenario: Probability of solar PV share according to different solar power investment costs for both low and high battery storage investment cost cases.

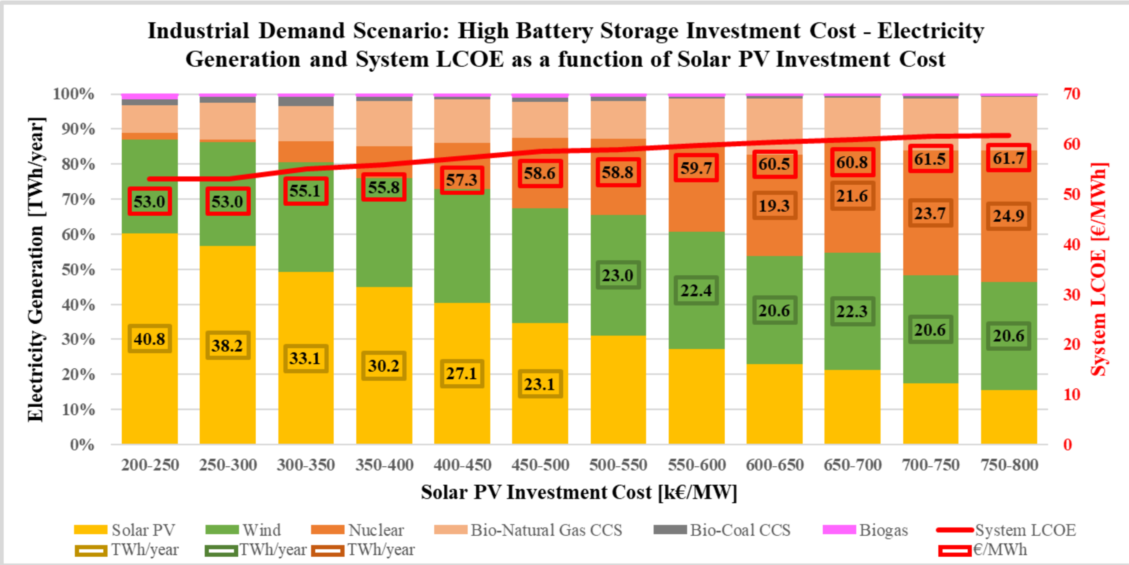

Figure A.20: Industrial Scenario: Generation mix and system LCOE at high battery storage investment cost. Only data labels for technologies with higher share than solar power are included.

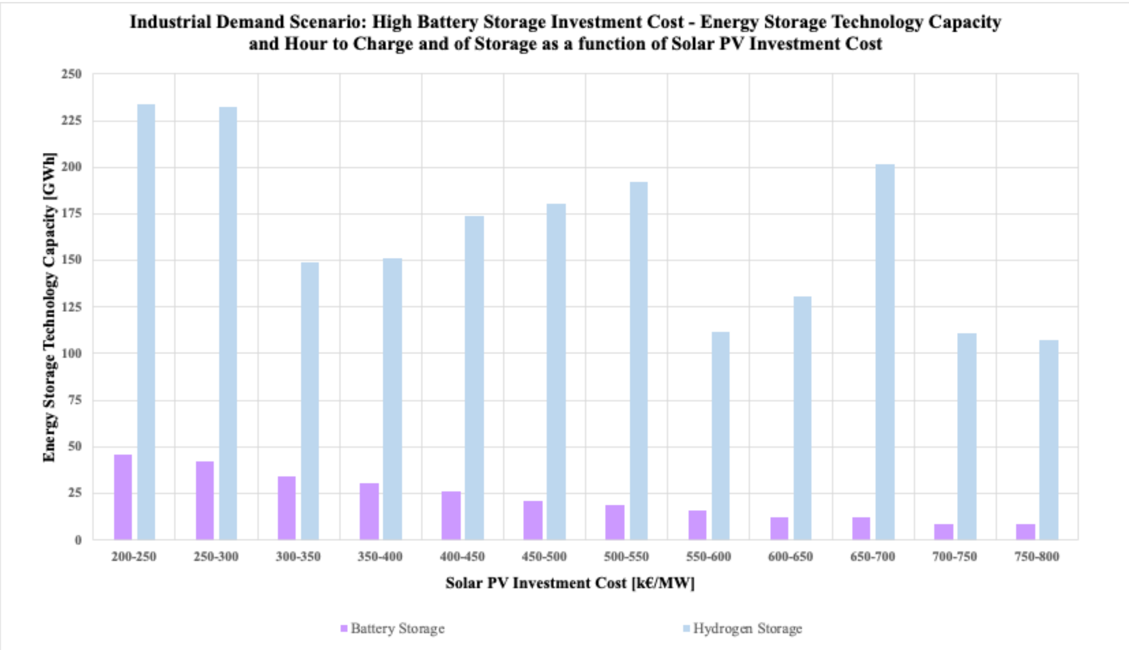

Figure A.21: Industrial Demand Scenario: Energy storage technology capacity and time required to charge and discharge a battery at high battery storage investment cost.

Table A.13: Investment cost for different solar power investment costs for the industrial demand scenario. L corresponds to low battery investment cost case and H corresponds to high battery investment cost case.

	Solar Power Investment Cost [k€/MW]	200-250	250-300	300-350	350-400	400-450	450-500	500-550	550-600	600-650	650-700	700-750	750-800
Wind Power [k€/MW]	**L**	1139.23	1171.96	1155.85	1151.5	1153.66	1097.08	1127.23	1155.28	1078.26	1141	1142.15	1147.89
	H	1188.02	1160	1105.48	1171.17	1149.06	1152.49	1105.69	1205.51	1173.78	1182.63	1172.28	1192.63
Battery Storage [k€/MWh]	**L**	90.97	93.21	93.4	90.89	86.47	91.66	84	79.61	93.19	86.56	89.04	96.7
	H	179.1	171.28	186.36	180.46	178.5	183.28	175.09	173.24	183.62	173.64	187.83	172.17
Battery Capacity [k€/MW]	**L**	142.1	133.35	148.73	163.98	148.45	130.13	170.88	159.88	138.97	164.53	135.88	154.87
	H	152.34	159.99	157.66	130.89	129.9	153.74	152.69	134.89	156.09	130.7	124.82	144.02
H_2 Storage [k€/MW]	**L**	4.33	5.73	5.61	6.71	5.53	6.74	6.56	6.26	5.99	6.76	5.92	6.91
	H	5.66	5.2	5.91	5.81	6.52	4.93	4.68	6.37	5.94	4.95	6.48	5.89
Fuel Cell [k€/MW]	**L**	769.32	849.55	794.52	778.74	782.25	807.28	801.54	821.16	800.64	837.57	809.95	776.91
	H	859.18	731.52	784.79	843.99	789.58	784.32	769.2	808.73	843.79	765.74	823.14	811.23
Electrolyzer [k€/MW]	**L**	536.61	530.91	520.9	578.82	504.4	563.06	497.81	540.18	506.02	547.9	531.98	538.11
	H	517.89	504.55	474.3	535.88	534.55	535.72	548.73	556.7	519.21	534.4	556.66	541.41

Table A.14: Fuel cost for different solar power investment cost for the industrial demand. L corresponds to low battery investment cost case and H corresponds to high battery investment cost case.

	Solar Power Investment Cost [k€/MW]	200-250	250-300	300-350	350-400	400-450	450-500	500-550	550-600	600-650	650-700	700-750	750-800
Nuclear [€/MWh]		6	6	6	6	6	6	6	6	6	6	6	6
Coal [€/MWh]	**L**	8.94	10.58	10.16	10.12	10.41	9.25	11.06	9.47	8.52	10.43	10.24	8.43
	H	10.19	8.76	9.99	8.91	9.49	10.01	10.19	9	9.39	9.52	9.36	8.87
Natural Gas [€/MWh]	**L**	31.35	37.11	35.64	35.49	36.51	32.45	38.8	33.22	29.9	36.59	35.91	29.58
	H	35.73	30.74	35.05	31.25	33.29	35.1	35.75	31.58	32.92	33.38	32.81	31.1
Biomass [€/MWh]	**L**	65.08	59.54	72.09	63.99	64.33	65.08	68.68	60.65	61.53	70.37	60.45	65.79
	H	55.29	55.67	64.36	61.81	64.78	64.84	68.75	58.73	69.64	65.89	61.21	67.01
Biogas [€/MWh]	**L**	112.97	105.06	122.98	111.42	111.89	112.97	118.11	106.65	107.9	120.53	106.36	113.98
	H	98.98	99.53	111.94	108.29	112.54	112.63	118.21	103.9	119.49	114.13	107.44	115.72

A.4.5 Sensitivity Analysis: Nuclear Power Investment Cost

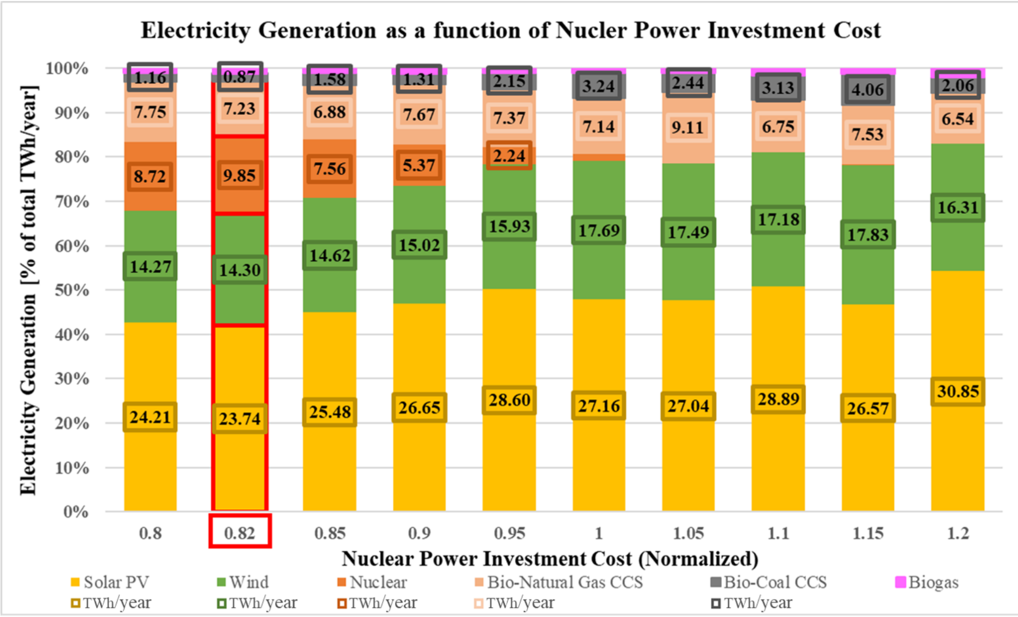

Figure A.22: Sensitivity analysis on nuclear power plant investment cost and its effect on total electricity generation mix. The transparent column with red border represents the average generation mix of the base scenario for the nuclear power investment cost of 4124 k€/MW.

Table A.15: Investment cost for different nuclear power investment costs for the sensitivity analysis.

Nuclear Power Investment Cost [k€/MW]	4000 (0.8)	4250 (0.85)	4500 (0.9)	4750 (0.95)	5000 (1)	5250 (1.05)	5500 (1.1)	5750 (1.15)	6000 (1.2)
Solar Power [k€/MW]	496.08	494.6	484.4	478.94	498.99	494.38	489.74	527.42	395.35
Wind Power [k€/MW]	1188,17	1126.58	1181.13	1152.68	1137.35	1164.16	1161.84	1189.17	1033.43
Battery Storage [k€/MWh]	135.31	133.33	131.13	130.70	140.92	143.83	135.35	134.94	148.1
Battery Capacity [k€/MW]	147.38	135.55	135.34	136.87	145.34	138.55	144.6	152.34	117.24
H_2 Storage [k€/MWh]	5.19	5.94	5.97	6.02	6.22	6.23	5.85	6	6.07
Fuel Cell [k€/MW]	807.52	754.24	805.14	810.87	792.24	816.31	816.52	825.13	838.2
Electrolyzer [k€/MW]	527.57	527.57	531.07	529.9	511.97	525.75	531.78	519.61	548.76

Table A.16: Fuel cost for different different nuclear power investment costs for the sensitivity analysis.

Nuclear Power Investment Cost [k€/MW]	4000 (0.8)	4250 (0.85)	4500 (0.9)	4750 (0.95)	5000 (1)	5250 (1.05)	5500 (1.1)	5750 (1.15)	6000 (1.2)
Nuclear [€/MWh]					6				
Coal [€/MWh]	9.64	9.9	9.27	9.77	10.21	9.36	10.21	10.03	10.36
Natural Gas [€/MWh]	33.81	34.73	32.53	34.28	35.81	32.83	35.83	35.18	36.33
Biomass [€/MWh]	66.74	65.16	61.89	65.8	64.98	67.39	62.26	63.83	56.27
Biogas [€/MWh]	115.35	113.09	108.42	113.99	112.83	116.26	108	111.19	100.38