Designing a future regional energy system

Multi-objective optimization for a regional energy system from a multi-actor perspective

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Challenge the future

Designing a future regional energy system: multi-objective optimization of a regional energy system from a multi-actor perspective

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Preface

This report marks the end of a five-and-a-half-month journey to finish my MSc. thesis for the Engineering and Policy Analysis programme at the Delft University of Technology and I am proud of the result. This report, however, also marks the end of my time as a student in Delft. It has been a truly incredible period in my life in which I had countless inspiring, fun, and amazing moments that I will never forget, both at the faculty of mechanical engineering, at TPM and away from the university. I would like to use this preface to thank some of the people without whom this thesis could not have taken shape.

First of all, I want to thank Ni for taking the time to guide me through an area of studies with which I was not familiar at all. We met every week and you were always able to guide me into directions I would not have explored otherwise. Thank you also for taking the time to review parts of my report throughout the entire process. I am grateful for your help and I hope that my work can be a strong contribution to your work and the field in general.

Secondly, I must thank Petra. Throughout the entire process, you were available to answer my questions and always provided very concrete feedback that helped me a lot. I especially want to thank you for taking the time to sit down with me to discuss the results I had and how to process them. When I was completely stuck deep in the data, your way of simplifying the most complex concepts helped me tremendously and I feel that this was a crucial moment in my research.

And of course, I want to thank Bert for being a part of my graduation committee and taking the time to provide me with valuable feedback on my research. I also want to thank you for your kind and positive attitude. I think the EPA programme has a crucial role in the TU Delft education and I hope that you continue to share your passion with your students.

I also owe gratitude to Thijs Wentink from HIER Opgewekt for taking the time to answer all my questions. The insights from someone who is directly involved in trying to speed up the energy transition were valuable and a critical part of my research.

I want to thank all the people that I met during my time in Delft. My friends for the necessary distractions, random moments, and all the amazing adventures that we went through. Last but not least, I want to thank the people without whom completing this thesis would not have been possible. Meyke, for your positivity and always wanting to help me and listen to me even when you were on the other the other side of the world. My parents for your support and the fact that you were always available, never too busy to pick up the phone or go for a walk and Pam and Joost for just being absolutely awesome. I had an absolutely amazing time in Delft and am looking forward to what is to come.

Pieter Imhof
Delft, September 2019

Executive summary

Research background and the main research question
At the end of June in 2019, the Dutch government presented the national climate accord. The accord concluded that the electricity sector will have to undergo a complete transformation: in 2030, at least 70% of all electricity in The Netherlands should come from a renewable source (Rijksoverheid, 2019). In the climate accord, the national government indicates that the energy transition cannot be managed only on a national scale and has formulated a Regional Energy Strategy. The challenges of spatial integration and acceptance will have to be solved on a regional level (Rijksoverheid, 2019, p.162). Developing energy systems on a regional scale (the scale of a large municipality or a combination of municipalities) will have to put flesh on the bones of the energy transition. The development of regional energy systems is also promoted from the bottom up: across the globe, regions have stated the ambition to be completely energy self-sufficient in 2050 or even earlier. In The Netherlands, 141 municipalities have stated ambitions to become energy neutral (BMC, 2018).

The road to reach these local and regional ambitions is not always clear, and there are many challenges involved in transforming a complex socio-technical system such as the energy system. Finding investors willing to pay the high capital costs involved (Bonacina, 2013), the heavy local resistance that developers of wind farms are facing (Cohen et al., 2014) and the high land requirements associated with renewable energy production (Zalk & Behrens, 2018) are three key barriers to a swift transition. One of the main issues in power system planning is defining the optimal mix of generation methods to fulfill the electricity demand: the generation mix. It is found that different stakeholders may, however, have a different view on the ‘optimal’ composition of the generation mix. These conflicting views on the optimal design are typical for a complex socio-technical system: the complexity of the challenge is increased by the different views of the involved actors.

Up to now, most studies have focused on finding a cost-optimal generation mix. The Dutch energy system functions as a liberalized market, so minimizing costs is important, but many studies neglect the complexity of satisfying the other interests of the stakeholders involved. This thesis presents a methodology to take multiple interests of different actors into account in finding the optimal generation mix for a regional energy system, leading to a design that is acceptable to all involved actors. It is a first step in bridging the gap between technical optimization studies into the cost-optimal system design of an energy system and the real-life issues that policy-makers, investors, and local communities are facing. The main research question that this thesis will answer is formulated as:

What is the most desirable generation mix for a regional energy system to meet the energy transition targets for 2030 and beyond, taking multiple objectives into account from a multi-actor perspective?

Actors involved in the energy transition
The energy transition is a complex process and many stakeholders are involved in the process of installing more renewable generation capacity. Four main stakeholder groups are determined to be most relevant in creating a sustainable regional energy system: governments, investors, local residents, and the consumers of electricity. Several levels of government are responsible for the licensing and the allocation of land for renewable generation capacity. The governments intend to ensure an affordable and secure supply of electricity while keeping the required land and visual impacts as low as possible. Investors also play a crucial role in the liberalized energy market. Investment decisions shape the generation mix, and the market will converge to a generation mix that maximizes the returns for investors. Local

residents want to minimize the visual impact of wind turbines. They can form organizations to protest the licensing of wind energy projects and possibly even fight the projects in court. Consumers are the final stakeholder. Their main interest is to have an affordable electricity supply. It is argued that minimizing *the total average cost of electricity, the investment costs, the land used for energy generation* and *the visual impact of wind turbines* will lead to a design that is better suited to the preferences of the different groups of stakeholders introduced in this section. These are the four criteria which will be minimized and based on which the desirability of a generation mix is evaluated. To find a generation mix that minimizes these four elements, a model is required. The model is discussed next.

The optimization model
To reflect on possible solutions to this problem, a multi-objective optimization model for a regional energy system is created. As a case-study, the region of Goeree-Overflakkee is analyzed using a genetic algorithm (NSGA-II). Energy in the region is provided by wind turbines, solar panels, biomass power plants, and through short-term energy storage. Flexibility is guaranteed through a connection to the national grid. Three different scenarios are investigated: reducing emissions by 70% to reach the national targets, reducing emissions by 90% to surpass the targets and reducing emissions by 98% to become almost fully self-sufficient as a region. No single design of a regional energy system is optimal regarding all four criteria mentioned above: the optimization results in a Pareto-front of non-dominated solutions for each scenario. Which of the solutions on the Pareto-front is most desirable is not directly clear: it depends on which criteria are most relevant in the region and the preferences of the involved actors.

Results
The results show that there are many designs possible for a future energy system. When emissions are reduced by 70%, no flexible generation in the region is necessary. Only wind and solar can be sufficient to fulfill demand. If 90% or 98% of the emissions needs to be avoided, flexible capacity from biomass energy or energy storage is required to be able to fulfill demand, because importing 'grey' energy when there is no sun or wind will lead to high emissions. Minimal cost, minimal land use, and minimal visual impact all increase significantly above an emission reduction of 80%. With increasing shares of renewable energy generation, the intermittent supply from wind and solar means that a significant amount of flexible capacity, overcapacity, or energy storage is required to be able to fulfill demand.

From the Pareto-fronts of optimal solutions, it can be observed that the composition of the generation mix has a significant effect on the four criteria. Land use may be reduced by increasing the amount of energy storage available in the region. This will, however, increase the electricity price if it is not subsidized. Analyzing the three different Pareto-fronts showed that there are significant trade-offs between the different criteria. Investors favor a solution with the lowest costs and will prefer a solution with a relatively high amount of wind turbines. Local residents will not be satisfied with this solution, however, due to the high visual impact of the wind turbines. Governments are concerned with minimizing land use and favor a design that includes more solar energy. In the scenario of 98% emission reduction, the optimal design for the governments also includes around 10% energy storage to reduce the required land.

The research question looks for a single optimal result: which of the solutions on the Pareto-front is most desirable? In this research, the average preference of all actors is argued to be a solution that is acceptable for all actors. Taking the average preferred result leads to a design that seems well balanced across all criteria. The average optimal generation mix in each of the scenarios is shown in figure 1 by evaluating the total annual cost incurred in the system for each technology. It is compared to the least-cost solution and the optimal solution for investors. The preferred solution clearly contains more solar energy than the least-cost solution in each scenario. Investors prefer a generation mix with more wind energy. A significant increase in investment is needed to reduce emissions from 90% to 98%.

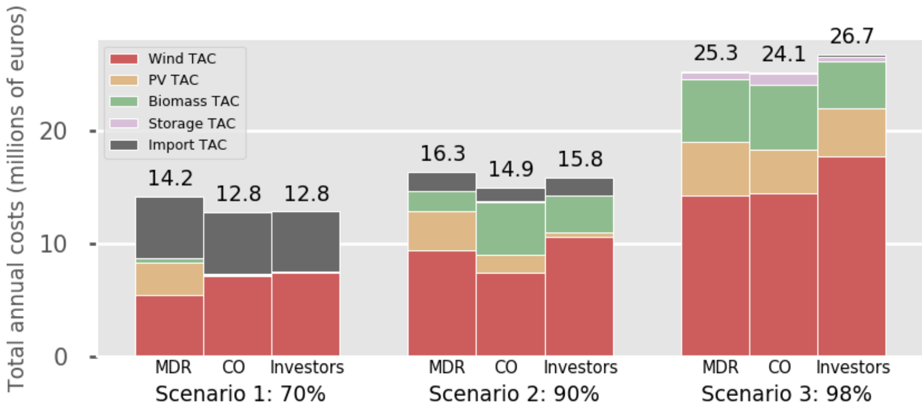

Figure 1: Comparing the Total Annual Costs (TAC) in the most desirable result (MDR) found in this research to the cost-optimal solution (CO) and the solution found to be optimal for investors. All three scenarios are shown here.

Discussion of the results

This research has shown that by including land use and visual impact as objectives in a multi-objective optimization, a solution can be identified that is more desirable to the involved stakeholders than a least-cost solution, but there are trade-offs to be made and the most desirable result is more expensive than a cost-optimal solution. Although energy storage can reduce the required land, it plays a small role in the preferred generation mix. Large steps are required in the technological development of energy storage before it is an efficient means of providing flexibility in a regional energy system.

Future land requirements for energy generation will be high and policymakers need to prepare for this. To reduce emissions by 90%, a quarter of the available land in Goeree is required. Goeree is not densely populated, and this challenge will be even bigger in other regions. Reducing the number of wind turbines in the generation mix comes at a high cost. In a liberalized electricity market, minimizing costs is crucial. To provide cheap electricity, wind turbines will play a big role in a future energy system. Power system planners should ensure the inclusion of all actors in the decision-making process to increase acceptance and make sure that all actors are heard and all interests are accounted for.

The results of this research show that investors prefer a high amount of wind turbines in the generation mix. This is confirmed by looking at real-life investment portfolios for big energy producers. The market will converge to an undesirable situation: the most desirable generation mix for all actors includes much more solar energy than the investors will want. Governments should take measures to promote the placement of utility-scale solar in their region to reduce the visual impact and land use. Also, they could implement policies that stimulate investors to invest in energy storage in the future.

Multi-objective optimization is a suitable way of approaching the design of an energy system in a complex socio-technical environment for two reasons. Firstly because there will always be conflicting interests in a socio-technical system and multi-objective optimization allows a modeller to take these into account. Secondly, a multi-objective optimization is interesting because it shows that there is not just one optimal solution. Many different designs are possible and can be compared to each other on their relative desirability. This way, the most feasible design can be found by engaging with stakeholders. As such, the model can be used to foster learning with decision-makers rather than dictate choice.

This research is a first step in including socially oriented objectives in an energy systems optimization and many steps are to follow. Two main contributions to the field are made. Firstly, this study has bridged the gap between energy systems optimization studies and socially oriented studies into the impacts of the energy system. The second contribution is methodological: it is shown that combining multi-objective optimization for an energy system with a multi-actor perspective can lead to more insight into the preferred situation for the involved stakeholders and can be used to find a solution that is, on average, most desirable.

Contents

List of Figures

List of Tables

List of Abbreviations

AI	Artificial Intelligence
CapEx	Capital Expenditure
DSM	Demand Side Management
DSO	Distribution System Operator
EES	Electrical Energy Storage
EPA	Engineering and Policy Analysis
FOM	Fixed Operational and Management costs
HDI	Human Development Index
IRR	Internal Rate of Return
LCOE	Levelized Cost Of Electricity
MCDM	Multi-Criteria Decision-Making
NGO	Non Governmental Organization
NPV	Net Present Value
NSGA-II	Non-dominated Sorting Genetic Algorithm II
PV	Photo Voltaics
RES	Regional Energy Strategy
RES-E	Renewable Energy Sources for Electricity
RRR	Required Rate of Return
TAC	Total Annual Cost
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TSO	Transmission System Operator
VIA	Visually Impacted Area
VOM	Variable Operational and Management costs
WACC	Weighted Average Cost of Capital

1 Introduction

At the end of June in 2019, the Dutch government presented the national climate accord. This accord lays out how The Netherlands intends to reach the goals formulated in the Paris agreement of 2015 to reduce the total CO_2 emissions by 49% before 2030. The accord concluded that the electricity sector will have to undergo a complete transformation: in 2030, at least 70% of all electricity in The Netherlands should come from a renewable source (Rijksoverheid, 2019).

In the climate accord, the national government indicates that the energy transition cannot be managed only on a national scale and have formulated a Regional Energy Strategy, which will have to put flesh on the bones of the transition. The challenges of spatial integration and acceptance will have to be solved on a regional level (Rijksoverheid, 2019, p.162). The development of regional energy systems is also promoted from the bottom up. Across the globe, regions have stated the ambition to be completely self-sufficient in 2050 or even earlier. The Danish island Samsø was the first region to become fully self-sufficient with regards to electricity in 2005 (Nielsen & Jørgensen, 2015) and has served as an example to regions around the world. In The Netherlands, 141 municipalities have stated ambitions to become energy neutral (BMC, 2018).

The road to reach these local and regional ambitions is not always clear, and there are many challenges involved in transforming a complex socio-technical system such as the energy system. For example, investments in the energy system are irreversible, capital intensive and long-lived (Bonacina, 2013), developers of wind farms in face heavy local resistance (Cohen et al., 2014) and producing renewable energy will require a large amount of land (Zalk & Behrens, 2018). One of the main issues in power systems planning is defining the optimal mix of generation methods to fulfill the electricity demand. Different stakeholders may, however, have a different view on what an 'optimal' situation would entail.

Up to now, most studies have focused on finding a cost-optimal generation mix. The Dutch energy system functions as a liberalized market, so minimizing costs is important, but many studies neglect the complexity of satisfying the large number of stakeholders involved. This thesis intends to analyze which other criteria are important in finding the optimal generation mix for a regional energy system and presents a method combining multi-objective optimization with multi-criteria decision making from a multi-actor perspective to find an optimal generation mix. This first chapter will set out to give context and the introduction to the problem.

1.1. Transition in the energy system

In the Paris climate agreement, 194 countries and the EU agreed to limit the global temperature to 2°C. The EU has implemented policies to limit the import of energy from high-risk countries by increasing the energy production in member states and diversifying the import routes (European Commission, 2014). Large transitions are necessary within the energy system to reach these goals, but energy transitions are slow and progressive processes (Smil, 2016). Even though the need to transform the energy system has been clear for decades, in 2016, only about 5% of the total world energy supply was from a renewable source (BP, 2018). In The Netherlands, the situation is not much better. Figure 1.1 shows that, although an increase is visible, in 2016 only 7.4% of all electricity came from renewable sources in The Netherlands. Out of all EU member states, The Netherlands is farthest away from realizing its renewable energy goals (Eurostat, 2019). The Netherlands currently imports over 35% of the electricity from abroad. This creates an external dependency and decreases the security of the energy supply (European Commission, 2018).

Over the last decades, many steps have been taken to develop Renewable Energy Sources for Electricity (RES-E). For a transition to happen successfully, the market needs to work in favor of renewable energy: renewable energy generation needs to be cost-competitive with conventional sources of energy. RES-E such as Photo Voltaic (PV) solar panels and on-shore wind turbines are the most promising for renewable electricity generation and are already cost-competitive with fossil fuel-based electricity generation (Chu & Majumdar, 2012). Hydropower, off-shore wind turbines and electricity generation from biomass are still more expensive, but prices are falling rapidly. In 2018, construction even started on the first offshore wind park in The Netherlands that is entirely unsubsidized.

All renewable methods are under constant development and costs are expected to keep going down (Chu & Majumdar, 2012). A projection of the cost per generated kWh for wind turbines and different types of solar energy is provided by IRENA (2018) and represented in figure 1.2. It can be seen that costs are already well within the range of fossil fuel alternatives: RES-E are already cost-competitive with their fossil-fueled counterparts, but the transition is only happening slowly. To understand the barriers involved, the next section will evaluate the energy system from a socio-technical perspective.

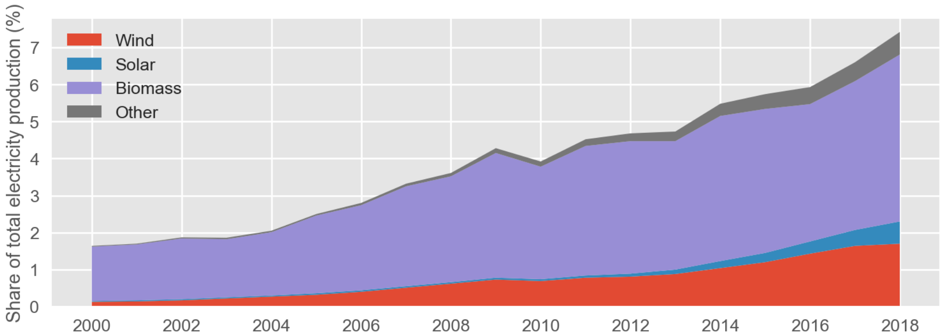

Figure 1.1: Shares of renewable electricity production in The Netherlands. Figure generated for this report based on data from CBS (2019a).

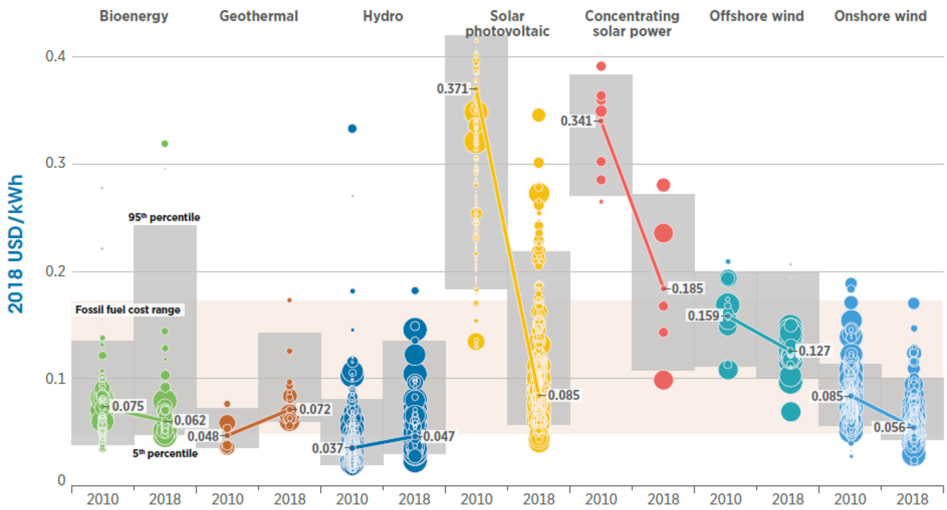

Figure 1.2: The prices of renewable sources of electricity from 2010 to 2018. The orange area represents the price range for conventional generation costs. Source: IRENA (2018)

1.2. Designing an energy system: a socio-technical challenge

From the previous sections, it is clear that a transition in the energy system is necessary, but transitions in such a large and complex system are inherently slow (Verbong & Geels, 2007). Although there are technological challenges, just looking at the technological side of the energy system does not fully explain the slow progress shown in figure 1.1: RES-E is already becoming cheaper than conventional generation and technological development is swift. To understand the slow prgress, a socio-technical perspective is necessary. The energy system and the involved technologies are firmly embedded in society: it is a socio-technical system that has both a technological and a social side which are strongly interconnected (Ellis, 2016; Wittmayer et al., 2017; Rae & Bradley, 2012; Späth & Rohracher, 2010; Verbong & Geels, 2010; Smith et al., 2005).

The consequences that changes in energy systems will have on society need to be emphasized to better inform policy debates (Miller et al., 2013). The energy system is heavily interconnected with society and the success of technological developments depends on many social and institutional factors. As a result of the strong interconnection between society and the energy system, many actors have an interest in the energy transition. They will have conflicting ideas about how the energy transition should take shape. The number of actors involved and the divergence of their interests are important determinants of the complexity of a problem (Enserink et al., 2010, p. 28).

Although costs are a critical consideration in designing an energy system for a liberalized energy market, finding a technically cost-optimal design for an energy system is a limited approach. Other preferences of the involved stakeholders should also be taken into account. Systems design for a socio-technical system should take both the social factors and the technological factors into account to make sure that the design can fully reach its intended goals (Baxter & Sommerville, 2011). This study intends to include some of the more social impacts of the energy system that are underrepresented in other studies. This section will discuss some critical barriers to the energy transition from the socio-technical perspective. Both technological and social barriers will be discussed. Several researchers have attempted to provide an overview of all relevant barriers (e.g. Painuly (2001)). In this introduction, only the barriers most relevant to this research will be discussed. The four barriers have been summarized in table 1.1. First, the technological barrier of balancing supply and demand with intermittent sources of electricity is introduced.

Table 1.1: Summary of the main technological and social barriers relevant to this research.

	Barrier
Technological	1: The energy **supply from RES-E is intermittent**. Because energy supply and demand always need to be perfectly matched, intermittent energy supply is a challenge when a high share of RES-E is included in the generation mix.
Social	2: **Local acceptance** from local residents to the placement of RES-E is a challenge to (mainly) wind farm developers: without local acceptance, local residents can prevent the placement of wind turbines in the region
	3: **Attracting investors** to finance RES-E projects is also a challenge. The investment costs for RES-E are relatively high and many investors still have a stake in fossil fueled power plants.
	4: A large **spatial integration** issue arises when a lot of RES-E is installed. Every square kilometer of land in The Netherlands has a purpose. RES-E has a bigger land requirement than conventional generation and locations for the placement of RES-E need to be found where the impact on the environment and communities is minimal.

1.2.1. Technological barriers to the energy transition: balancing supply and demand with intermittent renewable energy sources

Many technological elements of the energy system will have to be transformed. One of the most pressing challenges is balancing demand and supply in a system with intermittent energy supply. The two most promising sources of renewable energy, wind energy, and solar PV, are fully dependent on the weather for their energy output (Lund, 2007). Variability in the weather in different locations and different moments in time causes variability of the supply of energy. This variability in supply is called *'intermittency'*. Sometimes, the effect can be quite severe as can be seen in figure 1.3, which shows the capacity factor for wind power for four random days in June in The Netherlands. The supply can vary from 80% of the total available capacity to less than 10% in under 10 hours. The demand for energy follows general daily, weekly, and seasonal patterns and is not in sync with the pattern of energy supply (Walker, 2014). Energy supply by wind and solar is largely inflexible: the power output cannot be controlled. Total supply, however, must always exactly match demand and additional measures are needed to make sure that this is possible.

Several solutions exist to balance supply and demand in an energy system with intermittent sources of energy. Currently, flexibility is mostly guaranteed by flexible generation (e.g. gas-fired power plants) (Steinke et al., 2013). Flexible generation can be deployed when supply is low. Energy storage is another promising method to better match supply and demand, especially if combined with an overcapacity of RES-E. Installing overcapacity will increase the surplus of energy that can be stored (Weitemeyer et al., 2015). To be able to balance supply and demand, an optimal generation mix needs to be found. Finding the optimal generation mix will make it clear how much flexible generation, energy storage, and overcapacity is needed to be able to fulfill demand. In addition to this, the optimal generation mix will consist of different RES-E that may have complementary supply profiles, reducing the intermittency effects (Heide et al., 2010).

Several researchers have also indicated that by redesigning the grid for optimal RES-E distribution, the spatial variation in generation can be used to reduce intermittency (Becker et al., 2014; Brouwer et al., 2014). The weather is never the same over a large area, and this can be used to smoothen the supply profile if sufficient transmission capacity is installed. Demand Side Management (DSM) can also be used to better match the demand profile with the supply profile. Strbac (2008) gives several examples of techniques that can be applied.

The intermittency of the energy supply is a risk to a swift energy transition. Both the interconnected issues of the affordability of energy and the security of the energy supply could be at risk when renewable energy takes a larger share in the energy production: correcting for the intermittency may require significant investment in expensive energy storage, flexible

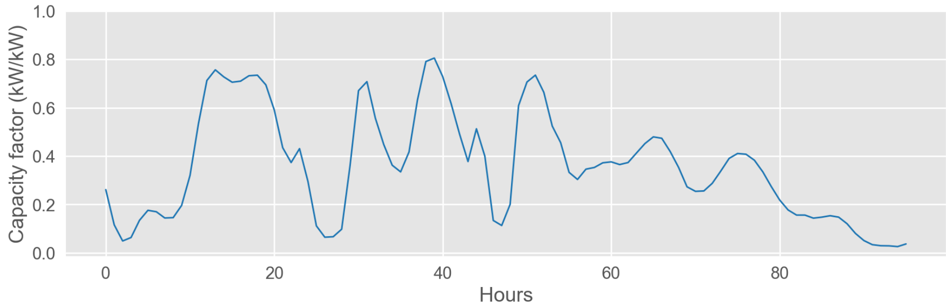

Figure 1.3: Generation from wind power in The Netherlands for four (random) days in June 2014. The figure was generated for the purpose of this report based on data from (Staffell & Pfenninger, 2016). The capacity factor on the y-axis is a measure for the output of the wind turbine as a share of the available capacity.

capacity or overcapacity. If not enough resources are invested in this flexibility, the security of the energy supply may be at risk. Balancing supply and demand is the only technological barrier considered here. The next section will investigate the most important social barriers relevant to this research.

1.2.2. Societal factors influencing the energy transition

As explained above, the energy system is a socio-technical system. Just looking at the technological challenges in the energy system leads to a design that may be theoretically accurate, but other factors need to be taken into account to ensure that the design can actually be implemented. The energy system is, in fact, a multi-actor environment. Many actors have an interest in the transformation of the energy system. They depend on each other in the realization of their objectives (Prasad Koirala et al., 2016). Actors may also have a different view on the optimal design of an energy system. This level of complexity is usually neglected (Bale et al., 2015). This research will set out to include the most important interests of different actors.

To better understand the challenges faced by different actors, this section will describe several of the main societal barriers to the energy transition. The list presented here is by no means meant to provide a complete picture of all barriers. Instead, the societal factors most relevant to this research are introduced. The main barriers are identified by looking at literature and through an interview with Thijs Wentink, who is part of a knowledge institute (HIER opgewekt) which focuses on aiding energy cooperatives and governments in realizing their energy transition targets. The source of information will be clearly indicated. If the information is from the interview with Thijs Wentink, it will be cited with: (Wentink, 2019). Several barriers will be introduced. Firstly, the challenge of local acceptance of RES-E will be introduced.

Local acceptance of RES-E

In creating a renewable energy system, local acceptance plays a big role (Mckenna, 2018; Müller et al., 2011; Wentink, 2019; Wüstenhagen et al., 2007; Zoellner et al., 2008). In the climate accord, this challenge is also emphasized and decentralized governments are tasked with ensuring that all new projects can count on sufficient acceptance (Rijksoverheid, 2019). In a future energy system, power generation will no longer take place in big, centralized power plants. Electricity will be generated in a more distributed way and closer to centers of population. Especially with the construction of wind farms, ensuring local acceptance of the construction of these wind farms is a significant challenge (Devine-wright, 2005; Wentink, 2019). If local residents do not agree with the placement of wind turbines near their homes, in their neighbourhood or their city, the project may not get a permit. Recently, conflicts between project developers of wind parks and local residents have taken extreme forms. Several project developers have even received death threats from residents who violently oppose the placement of wind turbines (RTL.nl, 2019).

Devine-wright (2005) indicates that, although the public support for integrating renewable energy is mostly high, due to multiple reasons, the support for the construction of actual wind farms is much lower. Abegg (2011) also found that debates about the installation of large RES-E installations and the land used by RES-E (instead of crop production) are a barrier to the implementation of RES-E. Promoting local financial participation, instead of distant corporate ownership is an excellent way to increase the local acceptance of wind farms and should be promoted (Devine-wright, 2005; Toke et al., 2008). Denmark has already successfully involved communities in renewable energy projects. Around 80% of Denmark's wind generation capacity is owned by some type of community partnership (Rae & Bradley, 2012). Even if sufficient local acceptance for an energy project is in place, another important barrier needs to be taken into account. Attracting investors is the second social barrier that will be discussed here.

Attracting investors for RES-E

For renewable energy projects, most costs are incurred before and during construction because the marginal costs of generating electricity are low. Although the total costs of generating electricity with RES-E are competitive, investment costs for RES-E are much higher than for conventional generation (Hirth & Christoph, 2016; Ondraczek et al., 2015). To be able to increase the installed capacity of RES-E, investors need to be attracted, and the high investment costs are a significant barrier to investors (Hirth & Christoph, 2016; Painuly, 2001; Wentink, 2019). Combine this with the ambition of the national government to ensure that local residents have a share of at least 50% in RES-E projects and the barrier becomes even more significant.

Projects to install RES-E also have a long lead time of 7 to 10 years between conception and the start of construction. Significant investments are needed before construction has even started. Environmental impact studies need to be done. Official proposals need to be made. Commitments from producers of wind turbines and solar panels are necessary. All without certainty that construction will actually take place (Wentink, 2019). This uncertainty ahead of construction deters investors. Investors into RES-E are more sensitive to this risk than investors in conventional generation because of the high up-front investment costs (Schmidt, 2014). The installation of RES-E is often faced with resistance, as is explained above. This is one of the reasons that a project may be rejected. Local resistance against wind turbines also deters investors who are concerned that projects may not get approval or face heavy (and expensive) resistance from local residents (Cohen et al., 2014; Wentink, 2019).

Another complicating factor is that many energy producers still have investments in conventional generation plants. These investments have not yet been written off, and the companies may not want to make new investments before the old investments have earned themselves back. Although in some situations, investing in renewable energy is even cheaper than only the marginal costs of conventional generation (KPMG, 2017b), big energy companies may still be reluctant to accept the lost investments in conventional generation (so-called sunk costs). If investments can be secured, space to install RES-E needs to be found. This is the next barrier that will be discussed.

Spatial challenges involved in the energy transition

Another key barrier to a swift energy transition is the high land use by RES-E (Rijksoverheid, 2019). This is an especially big issue because urban areas in The Netherlands have the highest ambitions regarding the energy transition (BMC, 2018). Both wind turbines and solar PV generation take up more land than conventional electricity generation in large plants: the energy density is lower (Gagnon et al., 2002; Nonhebel, 2005; Zalk & Behrens, 2018). Not only the quantity of required land is greater for RES-E, they are also often placed closer to densely populated areas: coal for coal plants can be mined in areas that are not densely populated and shipped to the power plant. Wind turbines and solar panels, however, need to be placed close to where the electricity is consumed because transporting electricity through transmission lines over long distances comes with high energy losses and high costs (ETSAP, 2014). Municipalities in The Netherlands are tasked with allocating land for RES-E and are overloaded with requests: they are having an increasingly hard time finding available land for RES-E (Wentink, 2019). In The Netherlands, all land is invariably used for some purpose and changing this purpose is a slow process. In the national climate accord, a separate chapter is dedicated to the challenge of land use. It states that in the energy transition, "sparse and where possible combined use of land" should be the goal (Rijksoverheid, 2019, p.180). Globally speaking, demand for land is likely to exceed the available land (Benton et al., 2018). The world's population will keep rising and feeding over 9 billion people will bring serious challenges. In the future, there may be a competition for land between energy production and food production (Harvey & Pilgrim, 2011). Some researchers even call the energy transition a mainly geographical process above anything else (Bridge et al., 2013).

To be able to solve the challenges mentioned above, several authors have argued that managing the challenge on a regional scale is more suitable than a national or international scale. Especially spatial integration challenges and acceptance issues can only be solved on a regional level (Rijksoverheid, 2019, p.162). The regional perspective to the energy system is now discussed in more detail.

1.3. Regional energy systems: an ideal scale for speeding up the transition

Droege (2009, p. 174) has argued that a regional scale is the perfect scale to lead the energy transition: "implementing policies and being decisive is easier on the regional level than the national level and regions are still big enough to transform individual motives into a powerful cooperation process". Droege even argues that regions across Europe should take up the gauntlet and set goals to become 100% self-sufficient. In a report commissioned by the Dutch government, this picture is confirmed: "regions are big enough to attract big investments, yet small enough to be a recognizable unit to companies and citizens" (VNG, 2017). The Dutch national government acknowledges the importance of regional development and the Regional Energy Strategy (RES) is a key part of the national climate accord (Rijksoverheid, 2019). The RES indicates that most challenges regarding spatial integration and local acceptance should be solved on a regional level. The 30 regions identified in the RES are to find locations and solve the spatial challenges involved. Approaching the energy transition from a regional level may help to increase the local acceptance for the construction of RES-E. In the Danish island Samsø, citizens felt part of the transition and cooperated to achieve the transformation into an energy self-sufficient island (Droege, 2009, p. 105). The willingness to pay may be higher if people are activated on a smaller scale: people may be more involved and willing to contribute to the energy transition (Prasad Koirala et al., 2016).

For what exactly constitutes a region, no single definition exists in literature. In this research, following the definition of Paris (2017) (among others), a region describes an area that is larger than a town, but smaller than a province (or state). In practice, this will be either a large municipality or a combination of several municipalities. This is an ideal scale of governance to speed up the energy transition. Large enough to gather enough investors and momentum, but small enough to be decisive and recognizable to the involved stakeholders. This scale of governance has proven to be very suitable to solve complex societal issues and has gained importance in recent years (Paris, 2017).

The national government has presented a top-down regional energy strategy, but to reach the goals set by the national government, bottom-up initiatives are also essential. The government leaves initiatives for renewable energy production to the market. In The Netherlands, 141 individual municipalities have stated ambitions to produce their own electricity and want to cooperate to reach these goals (BMC, 2018). There are several reasons for municipalities to declare these ambitions. Firstly, municipalities want to lead the energy transition and reach the targets set by the national government. In addition to this, they expect economic benefits (Müller et al., 2011), an increase in tax income (Engelken et al., 2016) and want to increase social cohesion (Abegg, 2011) by focusing on ambitious energy plans. Several regions have already made significant progress in the energy transition and ambitions are high. To provide some context to this research, some interesting regions that have high ambitions for the energy transition are discussed in appendix A.

Although 141 municipalities have stated goals to increase the degree of renewable energy, still only 7.4% of all electricity in The Netherlands is generated from renewable energy sources: ambitions are high, but progress is slow. This research will present an innovative approach to energy systems design that includes some social factors in determining the optimal design and takes the interests of multiple stakeholders into account. The next section will further introduce the problem statement and this research.

1.4. This research: problem statement, starting point and relevance to the EPA programme

This section will provide an overview of the research that is presented in this thesis. First, the problem is discussed. Finally, the research questions are formulated, and the structure of this thesis is presented.

1.4.1. Knowledge gap and problem statement

This introduction has introduced some of the challenges involved in reaching energy goals and the relevance of regional energy systems. Regional ambitions are high and the targets are clear: 70% of all electricity should be generated from a renewable source in 2030. The optimal mix of generation technologies to reach this goal, however, is not known.

Determining the optimal mix of generation technologies is important because of the intermittency of energy production from RES-E. Other factors such as local acceptance, spatial integration and attracting investors also influence the choice in generation mix. As will be seen in chapter 3, most studies investigating the optimal generation mix of an energy system only investigate a cost-optimal design: what is theoretically the cheapest way of providing energy in a future energy system? A single optimal solution is presented. This introduction has shown that other factors than cost influence the optimal design of an energy system. Only considering cost could lead to a solution that cannot be implemented due to socio-technical complications. As Slomp & Ruël (2000) pointed out: “a solution to a practical problem that cannot be implemented is not a solution”. Although the social aspects of the energy system are widely discussed in other fields of study, no effort has been made to include these factors in finding the optimal design of the energy system. Designing a system that takes into account some of the socio-technical barriers to the energy transition alongside the costs of energy has a much higher chance of actually being implemented than a purely cost-optimal design.

This thesis will present a methodology to take multiple interests of different actors into account in finding the optimal generation mix for a regional energy system, leading to a design that is acceptable to all involved actors. The issues of spatial integration and local acceptance will be important considerations in determining the optimal generation mix. A multi-objective optimization will be performed to find the optimal generation mix at different levels of CO_2 reduction. This thesis attempts to make a first step in bridging the gap between technical optimization studies into the optimal system design of an energy system and the real-life issues that policy-makers, investors, and local communities are facing.

To be able to do this, three main steps are taken: first, the involved actors and their interests are identified. From this, a set of critical criteria is found to consider when finding an optimal generation mix. Secondly, a multi-objective optimization model is created that incorporates this set of criteria. Thirdly, the resulting Pareto-front is analyzed to identify the optimal generation mix and the trade-offs to be made in selecting the generation mix. The main research question this thesis will answer is:

What is the most desirable generation mix for a regional energy system to meet the energy transition targets for 2030 and beyond, taking multiple objectives into account from a multi-actor perspective?

To be able to answer this main research question, some other questions also need to be answered. The sub-questions in this research are:

1. Which stakeholders are involved in the transition to a renewable regional energy system and what are their interests?
2. Which criteria should be considered when attempting to find an optimal generation mix?
3. How can an optimization problem be defined, taking into account the most important objectives of the actors?
4. What is the effect of the different elements of the energy system on the different criteria?
5. Which trade-offs between different criteria can be identified from analyzing the Pareto front?
6. What is the most desirable generation mix for different actors in each scenario of CO_2 reduction?
7. What is the benefit of including multiple objectives in the optimization other than cost?
8. What is the benefit of taking a multi-actor perspective to the optimization of an energy system?
9. What are the most important implications for policy-makers from this research?

1.4.2. The starting point of this research

The optimal generation mix for a Dutch regional energy system will be determined in this research. For this, a new optimization model has been created and an innovative way to process the results of the multi-objective optimization will be proposed. In section6.1, a typical rural region (Goeree-Overflakkee) is introduced on which the analysis will be based. Goeree-Overflakkee already has a significant amount of wind turbines. In this research, this is not taken into account: the optimal generation mix is determined with the assumption that there is no RES-E in the region and there is a central planner. Several limitations of this approach will be discussed in section 9.2.

Although some studies analyze energy systems from a stand-alone perspective, it is assumed that flexibility can at all times be guaranteed by a connection to the national grid. This is the most realistic approach. Studies analyzing stand-alone systems usually use diesel generation to ensure flexibility on a regional scale. No Dutch region will realistically use diesel generators to supply large amounts of electricity if grid connection is also an option. Several limitations of the assumption that energy can at all times be importer will be discussed in section 9.2.

1.4.3. Relevance to the EPA programme

This thesis was written to obtain the MSc. degree for the Engineering and Policy Analysis (EPA) programme at the Delft University of Technology. EPA is focused around working on grand international challenges and taking a multi-actor perspective to socio-technical systems. At EPA, one of the main aims is to inform policymakers through modelling techniques and to bridge the gap between technology and society. This research aims to make a contribution to the grand challenge of the energy transition and to bridge the gap between the technological optimization models and some more social studies that have been done into the effects that the energy transition will have on society. Advanced modelling techniques are applied to learn more about the functioning of the complex socio-technical energy system. A multi-actor perspective is taken to learn more about the preferences of the involved stakeholders and to come to a solution that is most acceptable to all stakeholders. In this way, this thesis represents a good fit to the EPA programme and the knowledge I gained from following the EPA programme regarding modelling, researching stakeholders and policy processes has made it possible to write this thesis. The structure of this report will now be shortly introduced.

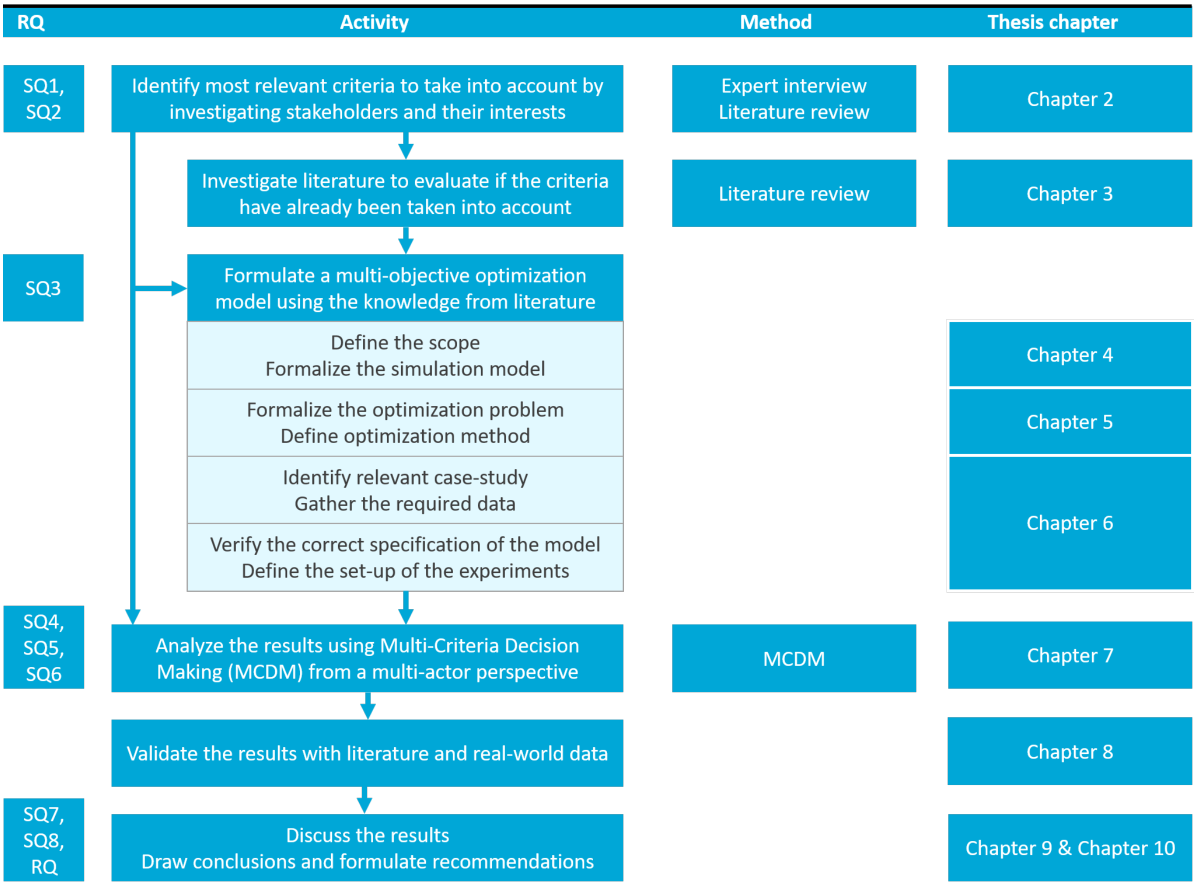

Figure 1.4: Structure and flow of this research.

1.5. Structure of this report: a reading guide

A full reflection on the performed research is provided in this report. The methodology that is used and the further structure of this report is represented as a flow diagram in figure 1.4. This introduction has provided background information on the research, introduced the energy system as a socio-technical system, and introduced the research questions. Chapter 2 investigates the actors involved in the regional energy transition and their most important objectives. From this, the most relevant criteria to take into account when designing an energy system are determined. Chapter 3 gives an overview of the most relevant literature and will introduce some of the most relevant concepts in energy systems modelling. A clear research gap is formulated, which will be the starting point for the next chapter. In chapter 4, the model is introduced. The model consists of two parts: a simulation part and an optimization part. Chapter 4 will provide the mathematical formulation of the simulation model. Chapter 5 defines the optimization problem used to find the optimal design. After the optimization problem has been defined, the method used to solve the optimization is presented and explained. Up to now, the model that has been created is generic: it can be used to find an optimal design for any regional energy system. In chapter 6, the case-study is introduced and the data inputs that are used in the optimization are discussed. Also, the scenarios used in the optimization will be introduced. The results of the optimization are presented in chapter 7 and compared to a cost-optimal design. Having presented the results of the optimization, the results are subsequently validated against previous work and real-life data and tested for sensitivity in chapter 8. Also, the validity of the case-study is discussed. After the results have been validated, the implications of the results to power system planners and some limitations are discussed in chapter 9. Finally, chapter 10 presents the answers to the research questions and some recommendations for further research.

2

Stakeholders and criteria to consider in finding the optimal generation mix

As was stated in the introduction, the electricity market is undergoing a major transformation. The relevance of transforming the energy system with a focus on a regional scale has also been shown. Several important societal barriers were introduced. This chapter will set out to identify the most relevant actors that play a role in the regional transformation of the energy system. Based on the interests of these actors, the most important criteria to take into account when designing an energy system will be identified. First, an introduction to the Dutch energy system is provided to be able to identify the most important actors.

2.1. The Dutch electricity system

The energy system in The Netherlands has undergone major changes over the past decades. The current Dutch electricity system functions based on market principles, but this was not always the case. Before a new law was passed in 1989, the electricity system was centrally controlled by the government (Verbong & Geels, 2007). Since the 1990s, the electricity market in The Netherlands has become more liberalized, operating based on market principles. The system has been summarized in figure 2.1, which has been simplified for the purpose of this research.

The figure shows how producers of electricity can sell electricity on the electricity market to retail companies. The retail companies sell it again to consumers. Several retail companies trade only renewable energy and some retail companies have their own production capacity. In The Netherlands, 75% of all electricity is sold as renewable energy (WISE Nederland, 2019). In the previous chapter, however, it was already pointed out that only 7.4% of the electricity is from RES-E in The Netherlands: most electricity that is sold as renewable energy in The Netherlands is actually produced abroad.

In figure 2.1, it is also shown that the transmission of electricity is done by regulated system operator companies. The Transmission System Operator (TSO) is responsible for the high voltage transmission network and the balancing of the demand and the supply off electricity. To balance demand and supply, the TSO is also active on the electricity market and contracts back-up capacity with the producers and regulates the national imports and exports of energy. A comprehensive summary of how the TSO balances supply and demand in The Netherlands is provided by Agro Energy (2017). Several Distribution System Operators (DSO) are responsible for the (lower-voltage) distribution of electricity on a regional level.

Now that a short overview of the Dutch Electricity system has been discussed, the actors involved in creating a regional energy system will be discussed.

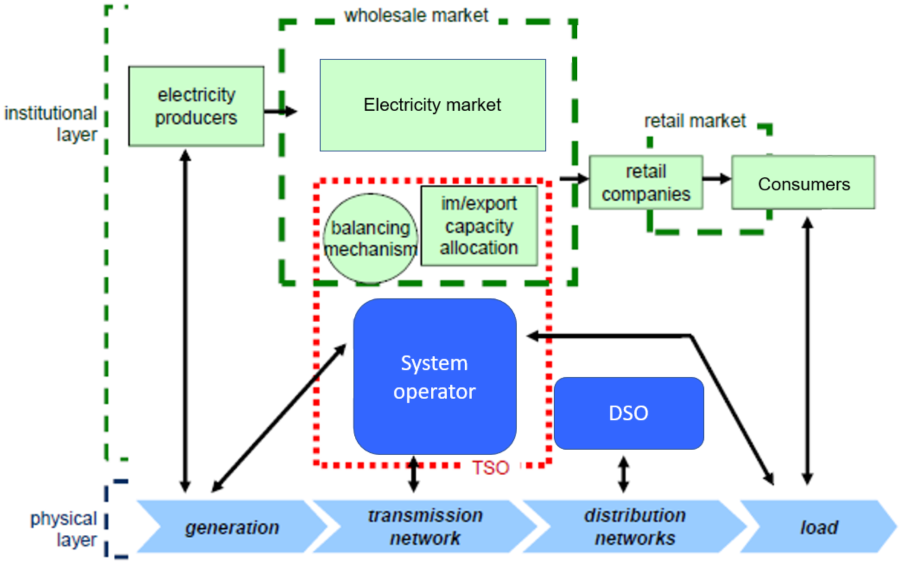

Figure 2.1: Summary of the electricity system in The Netherlands simplified and adapted from De Vries et al. (2018, p. 5). The institutional layer describes the actors and institutions that act on the electricity market. The physical layer shows how these actors interact with the physical infrastructure of the energy system.

2.2. Actors involved in the transition to a regional energy system

The actors involved in creating a regional self-sufficient energy system will be discussed in this section. The goal of this actor scan is to identify the most relevant actors in creating a regional energy system and their interests. The actors have been identified from literature and the interview with Thijs Wentink. Retail companies have not been included in the actor scan. These are mainly profit-oriented and the consumers dictate the success of the different retailers. Therefore, the consumers have been included, but the retailers have been left out. Table 2.1 shows the most important interests, objectives, and resources of all the relevant actors. The interests of an actor describe the issues that matter most to an actor regarding the energy transition; they are stable and not directly linked to creating a self-sufficient region. The objectives describe concrete goals that the actor wants to achieve related to the energy transition. The resources of an actor describe the means available to an actor to achieve their objectives. In addition to the summary provided in table 2.1, all the actors have been discussed more thoroughly below. It should be emphasized that the energy transition is a very complex process and the actors and objectives presented in this chapter are inevitably a simplification of the real-world situation. The most relevant interests and resources to this research are included.

Firstly there is the **national government**. The classical energy goals of the national government consist of three parts: provide a reliable supply of energy, maintain the affordability of electricity and have an environmentally friendly electricity system (De Vries et al., 2018; Bale et al., 2015, p. 3). The national government, however, also has other interests. The national government has acknowledged the spatial challenges that exist and indicates that the responsibility to solve the spatial challenges lays with decentralized (provincial and municipal) governments (Rijksoverheid, 2019; VNG, 2017). In the climate accord, it is indicated that land use should be as sparse as possible (Rijksoverheid, 2019, p.180). The national government also indicates that acceptance is a key issue in the energy transition. They want to ensure that the acceptance of RES-E projects is taken into account (Rijksoverheid, 2019). Again, the national government transfers the responsibility for this to decentralized governments and indicates that the Regional Energy Strategy plays a key role in this (Rijksoverheid, 2019, p.162). The Dutch government has stated that participation is essential in creating more acceptance and has formulated the objective that 50% of all RES-E projects should be in the hands of local citizens.

The national government has several policy options, such as promoting the use of RES-E

Table 2.1: Overview table for interests, objectives and resources for all relevant actors

Actors	Interests	Objectives	Resources
National government	Safeguard energy security Maintain affordability of electricity Achieve Paris climate goals Ensure local acceptance Ensure proper spatial integration	Achieve 70% renewable in 2030 Minimize cost per kWh Maximize reliability of supply Minimize land used for RES-E Minimize visual impact and noise from RES-E Increase public ownership of RES-E Limit spending on subsidies	Introduce subsidies for RES-E net-metering, feed-in-tariffs Support innovations Provide licensing for big RES-E projects (>100MW) Possible: regulation to secure peak-load response
Provincial government	Safeguard energy security Maintain affordability of electricity Ensure local acceptance Ensure proper spatial integration Achieve the goals set by national government	Achieve 70% renewable in 2030 Minimize land used for RES-E Minimize visual impact and noise from RES-E Maximize reliability of supply Minimize cost per kWh Increase public ownership of RES-E	Allocate land for RES-E projects Licensing of smaller RES-E projects (10-100MW) Cooperate with cooperatives, companies and municipalities
Municipal government	Safeguard energy security Maintain affordability of electricity Ensure local acceptance Ensure proper spatial integration Achieve the goals set by national government Ensure involvement of all stakeholders	Achieve 70% renewable in 2030 Minimize land used for RES-E Minimize visual impact and noise from RES-E Maximize reliability of supply Minimize cost per kWh Increase public ownership of RES-E Increased job creation in the region Increase the social cohesion	Allocate land for RES-E projects by changing destination plans Support energy cooperatives financially or organizationally Support sustainable housing Licensing of smaller RES-E projects (<10MW)
Large producers of electricity	Generate profit for shareholders	Maximize return on investment in RES-E Minimize investment cost Protect investment in conventional sources Reduce emissions from energy generation Minimize cost per kWh Minimize investment risk	Financial investments in RES-E projects Provide technical know-how surrounding RES-E
Consumers of electricity	Minimize cost of living Sustainable and stable energy supply	Minimize cost per kWh Minimize CO_2 emissions from electricity use Maximize reliability of supply	Choose energy supplier based on price and sustainability Vote for government (municipal, provincial, national) Join NGO or energy cooperative Invest in PV or Wind generation (and EES) for personal use
Local residents against RES-E	Prevent negative effects of RES-E projects	Minimize the visual impact and noise from RES-E	Exert pressure on the municipal and provincial governments to influence licensing of RES-E projects Fight RES-E projects in court
Energy cooperatives	Full transition to RES-E profit for members	Increase the RES-E penetration Maximize return on investment Minimize investment cost Increase public ownership of RES-E Minimize cost per kWh Minimize investment risk	Invest in RES-E Exert pressure on the municipal and provincial government to support RES-E
Land owners	Financial gain and protect living environment	Maximize return from RES-E on their land Minimize land used for RES-E	Invest in RES-E on their land Protect their land from the placement of RES-E if compensation is not enough
TSO	Secure energy supply for citizens	Maximize peak-load response performance Maximize reliability of electricity supply	Demand regulation to ensure sufficient flexibility and investment in transmission
DSO	Secure energy supply for the region	Maximize peak-load response performance Maximize reliability of electricity supply	Demand regulation to ensure sufficient flexibility and investment in transmission

by introducing subsidies (the so-called "SDE+"subsidy) or Feed-In-Tariffs and Net-metering. The national debt is already 56% of GDP and the government does not want to increase this debt. Therefore, the amount of subsidies provided should not exceed the planned amount. The national government is responsible for the regulations around big RES-E projects. For wind energy, the national government is responsible if a project is bigger than 100MW (Rijksdienst Voor Cultureel Erfgoed, 2019). Because this research approaches the energy transition on a regional level, the national government will be evaluated as one institution. In reality, however, the national government is made up of several departments that may all have their own interests.

The **provincial government** is responsible for allocating land to RES-E projects. The provincial government is also responsible for giving permits and solving spatial integration issues around smaller RES-E projects. For wind energy, this is 10 to 100MW (Rijksdienst Voor Cultureel Erfgoed, 2019). The interests of the provinces are aligned with the interests of the national government in the energy transition. The affordability, energy security, and sustainability are all important factors. Minimizing land use will make spatial integration easier and minimizing the impact on local residents will increase local acceptance. Some provinces like Zuid-Holland have said that it is not the aim to become completely self-sufficient with regards to electricity on a provincial level due to the high population density (Provincie Zuid-Holland, 2020).

The **municipal government** is also an important actor. The interests of the municipality also have similarities to the interests of the national government. The municipal government intends to reduce the CO_2 emissions, guarantee affordable electricity, and to increase energy security. However, they may have some extra interests, such as economic growth in the region, job creation, and increased social cohesion (Abegg, 2011; Engelken et al., 2016). The resources of the municipal government mainly consist of the stimulation of renewable initiatives in their municipality and supporting energy cooperatives, discussed below, with financial resources or organizational support. Importantly, municipalities are also responsible for allocating land for RES-E projects (PBL, 2017). Municipalities are at the forefront of solving spatial issues regarding smaller (<10MW) RES-E projects and finding land is a big issue for many municipalities (Wentink, 2019). Therefore, solutions that require less land will be more favourable. Municipalities, together with provincial governments, are also responsible for making sure that the acceptance of new RES-E projects is taken into account (Rijksoverheid, 2019). Minimizing the visual impact of RES-E will increase acceptance. In this research, municipalities are assumed to have similar interests. In reality, however, the interests of different municipalities will vary. Some municipalities have high ambitions and support the placement of wind turbines. Other municipalities are unhappy with the demands of higher levels of government to put wind turbines in their municipalities (PBL, 2017).

Several big companies are **producers of electricity** that sell electricity on the electricity market. In The Netherlands, big companies such as Nuon/Vattenfall, Engie and Essent are the producers of electricity. Their interests are mainly to maximize profits and increase value for their shareholders (VNG, 2017; Wentink, 2019). They want to minimize the price of generating electricity and maximize the returns on their investments. The big, multinational, producers have significant investments in conventional power generation plants and may want to protect these investments: they do not want to invest in new projects before the investments in the old projects have earned themselves back. Most RES-E projects also require an investment from a bank or other parties. RES-E have a high investment cost (Hirth et al., 2015). This increases risk and makes attracting investors more difficult (Wentink, 2019). Energy producers will want to minimize the investment cost to be able to attract investors. Although most energy companies are mainly profit-oriented, several producers (such as Eneco) are very proactive in the energy transition (Hufen & Koppenjan, 2015). Not all producers of energy are large energy companies. There are also many small 'prosumers': citizens who generate their own energy, usually through roof-mounted solar panels. This research, however, approaches the energy system from the perspective of a central investor/planner.

This is a necessary simplification (see 1.4.2). Therefore, the prosumers have not been taken into account.

The consumers of electricity (mainly households, but also large industrial consumers) also have several interests. They demand a reliable supply of electricity. The main interest of most consumers is economic in nature: they want to save money before all else. A minimal cost of electricity is their main goal (Islar & Busch, 2016). Although cost is the most important driver for consumers, buying sustainable electricity is also relevant to consumers. In 2017, 69% of consumers chose a producer that offered them green energy (ACM, 2017). The most relevant resource of consumers is choosing from whom they buy their electricity, thereby putting pressure on the producers to keep costs low and invest in RES-E.

Local residents protesting against the installation of RES-E compose another actor. Local acceptance is a big factor when it comes to installing wind turbines or other big installations near populated areas (Zoellner et al., 2008; Hall & Ashworth, 2013; Wüstenhagen & Menichetti, 2012; Wentink, 2019). Action groups protesting mainly the placement of wind turbines is a well-documented occurrence in The Netherlands (Jongebreur, 2016). Usually, these organizations are locally organized and protest the placement of specific wind turbines. Their interests are quite one-dimensional: preventing the adverse effects of the placement of wind turbines. Most groups are mainly concerned about the visual impact of wind turbines. Protests in The Netherlands have recently taken very extreme forms. Emotions are running high, and project developers of wind farms are even receiving death threats (RTL.nl, 2019). Because of the considerable resistance, participation and inclusion in decision-making are critical. The interests of local residents have to be taken into account. In this research, the consumers and residents are two different actors: consumers are the buyers of electricity, local residents are against the placement of RES-E in the region.

There are also **NGO's in favor** of the transition to RES-E. These are either organized internationally (such as IRENA) or nationally (such as Urgenda). On a regional level, proponents of RES-E usually do not decide to start lobbying. A more effective tool of promoting RES-E is by creating an energy cooperative, which will be discussed next. Therefore, these organizations have not been included in this analysis.

On a local and regional level, **energy cooperatives** are playing an increasingly large role in producing renewable electricity (Hufen & Koppenjan, 2015). Over the last ten years, almost 500 cooperatives, involving almost 70.000 citizens, have been started in The Netherlands (HIER, 2018). Cooperatives are local initiatives in which citizens can take a stake. They invest the contributions in RES-E. Now that the government has set targets to have at least 50% of new RES-E projects in public hands, the role of energy cooperatives will become even bigger (Wentink, 2019).

Their main goals are to provide their investors with as much interest as possible (Viardot, 2013; Wentink, 2019), to speed up the energy transition and to increase the influence of local citizens (Van Der Veen, 2016; Wentink, 2019). They intend to maximize the returns on investment and minimize the price of generating electricity. They also provide citizens with information and education about RES-E (Viardot, 2013; Wentink, 2019). Several of these energy cooperatives already produce electricity, which is sold on the energy market. Energy cooperatives are a relatively new phenomenon but already produce enough electricity to power 140.000 households in The Netherlands.

One of the biggest cooperatives in The Netherlands is DeltaWind in Goeree-Overflakkee. Citizens can loan the cooperative a maximum of 5000 euro, and DeltaWind invests in wind energy. Citizens receive interest and DeltaWind has already succeeded in producing enough electricity for all 15.000 households of Goeree-Overflakkee (Hufen & Koppenjan, 2015). DeltaWind is used as an example here. Not all cooperatives focus solely on wind energy, however. Other examples are Texel Energie in Texel, Grunneger Power in Groningen and Lochem Energie in Lochem (Hufen & Koppenjan, 2015).

The construction of RES-E will require land. **Land owners** are therefore also a stakeholder in the construction of RES-E (VNG, 2017). In The Netherlands, the land on which wind turbines are placed is usually owned by farmers. Research suggests that land-owners are usually quite positive towards the placement of wind turbines if they are involved in the process and receive financial compensation (Mills et al., 2019). Their interests are mainly financial: they want to maximize the profits from RES-E (VNG, 2017). In The Netherlands, farmers mostly see wind turbines as a way to make money even develop RES-E on their own initiative (Bouma, 2019). Land owners are not necessarily farmers, however. Businesses that own large buildings with flat roofs to put solar panels on, can also be considered land owners.

The **TSO** also has a stake in the energy transition. In The Netherlands, this is TenneT. The interest (and the responsibility) of the TSO is to transfer electricity from the location of production to the location of consumption and to balance supply and demand. Their objective is to have the highest possible reliability of the power supply. The TSO needs enough back-up power, storage, or the possibility to take electricity from the national, centralized grid in times of peaking load: they want to guarantee the peak-load performance. The TSO also needs sufficient funding to be able to maintain the grid.

The TSO cooperates with several local **DSO's** that are responsible for the infrastructure to secure local power distribution. They are also regulated by the government. The interests of the DSO's are to secure proper electricity infrastructure and maintenance.

From this section, it can be concluded that many different actors are involved in creating a regional energy system. From identifying the actors and their interests, the most important criteria to take into account in selecting the optimal generation mix for a regional energy system are identified in the next section.

2.3. Criteria to take into account when choosing a generation mix

This research will perform a multi-objective optimization for a regional energy system. From the previous sections, it is clear that just including total costs in an optimization for an energy system oversimplifies the situation: the involved stakeholders have many other interests. The most important objectives of the actors should be taken into account when designing an energy system. Section 2.3.1 will show that six criteria are found to be most important to the involved actors. These criteria will be discussed in more detail in sections 2.3.2, 2.3.3, 2.3.4 and 2.3.5. As will be argued below, two criteria are not suitable to compare different compositions of the generation mix. Four criteria remain that are summarized in section 2.3.6. First, however, the categorization of the interests of the actors is explained.

Table 2.2 shows all the criteria that are relevant to the different actors identified in table 2.1. The criteria are divided into four categories to create some more structure. These categories are: economic, environmental, social, and technological criteria. *Economic* criteria concern the criteria that have to do with the cost of the system and the attractiveness of the investment. *Environmental* criteria represent the effects that the energy system may have on the environment and wildlife. The *social* criteria concern all criteria that describe the effects of the energy system design on surrounding communities. Finally, *Technological* criteria concern all criteria that represent the technological side of the energy system. A selection of the most relevant criteria needs to be made: only the most important objectives can be taken into account. The next section will elaborate on this selection.

2.3.1. Selection of the six most relevant criteria to the involved actors

The actors have several different interests, but only the most relevant interests are included in further analysis. The most important interests of the actors need to be represented in the selected criteria. Also, criteria that are not directly influenced by the composition of the generation mix, but mainly by contextual factors are not as relevant to finding the optimal generation mix, and are left out of further analysis. The choice in criteria is motivated shortly here, and discussed in more detail for the individual criteria below. The six criteria that are taken into account in this research are represented in bold in table 2.2.

Table 2.2: Showing the preferences of the different actors for each of the objectives mentioned in table 2.1. The six most important criteria that are used in this research are represented in bold. *(NG = National Government, PG = Provincial Government, MG = Municipal Government, Prod. = energy producers, Cons. = Consumers, LR = Local Residents, Coop. = energy Cooperatives, LO = Land Owners)*

		NG	PG	MG	Prod.	Cons.	LR	Coop.	LO	TSO	DSO	#
Economic												
	Minimize costs per kWh	√	√	√	√	√		√	√			*7*
	Maximize returns				√			√	√			*3*
	Minimize investment cost				√			√				*2*
	Minimize investment risk				√			√				*2*
	Limit spending on subsidies	√										*1*
Environmental												
	Reduce emissions	√	√	√	√	√		√				*6*
Social												
	Reduce visual impact and noise	√	√	√			√		√			*5*
	Minimize land use	√	√	√					√			*4*
	Increase public ownership	√	√	√								*3*
	Increase social cohesion			√								*1*
	Increase job creation			√								*1*
Technological												
	Reliability	√	√	√		√				√	√	*6*
	Peak-load response									√	√	*2*

Three economic criteria are most important to the involved actors: minimizing costs per kWh, maximizing the returns and minimizing investment costs. These will be discussed in more detail below. Minimizing the risk of investment and limiting spending on subsidies is only important to a few actors and other contextual factors are a bigger determinant for these criteria than which technologies are included. Therefore, this is not taken into account.

Reducing the CO_2 emissions is important: most actors are aligned on the ambition to create a more sustainable energy system. This is a critical environmental consideration.

The two social criteria of reducing visual impact and the land used for energy generation are important to several actors and also play a crucial role in the barriers introduced in table 1.1. Visual impact and land use will be taken into account in this research and are discussed below. Public ownership, social cohesion, and job creation are also important social criteria to some actors. The success on these three objectives, however, does not depend only on the composition of the generation mix, but mainly on contextual factors. Therefore, these have been used to find the most desirable generation mix in this research.

No technological criteria will be taken into account in this research. This choice is motivated below in section 2.3.5.

This research presents a unique perspective by looking at the actual objectives of the involved actors to evaluate which criteria to take into account. To be sure that no critical criterion is left out, a literature study was also performed to evaluate which other criteria have been considered in literature. Several studies, most notably Al-falahi et al. (2017), Østergaard (2009), Østergaard (2015), Santoyo-castelazo & Azapagic (2014), Tezer & Yaman (2017) and Antunes & Henriques (2016, p. 1132), provide an overview of important criteria to be taken into account. Quite an extensive review of possibly relevant criteria was performed for the purpose of this research, and other criteria may be relevant to other researchers. Therefore, a discussion of these criteria is provided in appendix B.

The following sections will discuss the six most relevant criteria in more detail and will introduce metrics based on which the criterion can be evaluated. It will be argued that two out of the six criteria cannot be used to evaluate the desirability of the generation mix. Four critical criteria are identified and summarized in section 2.3.6.

2.3.2. Economic criteria

Economic considerations are important considerations when making an investment decision for the power system. Many actors are concerned with keeping the electricity supply affordable, and the market will steer towards a cheaper alternative. This section will discuss several economic criteria, starting with the total costs per kWh.

Minimizing costs per kWh: Levelized Cost Of Electricity (LCOE)

Several costs are involved in generating electricity. Almost all stakeholders are concerned with keeping the costs of energy as low as possible. To determine the total costs for generating electricity, a measure called Levelized Cost Of Electricity (LCOE) is usually used.

The LCOE is a measure for the "discounted life-time fixed and variable cost of a generation technology in €/kWh" (Edenhofer et al., 2013). In other words, the LCOE can be calculated by dividing all (discounted) costs incurred in the generation of electricity over the life-time of a power plant by the total electricity that a power plant generates.

On average, each electricity plant has to sell electricity at a price equal to or slightly higher than its specific LCOE to be able to earn back the initial investment over its life-time. The LCOE, therefore, has an impact on the price of energy for consumers. The higher the system LCOE, the higher the market price of electricity will be, the higher the energy bill for the consumers will be (Østergaard, 2009). Because of this, it is in the interest of most actors to keep the LCOE as low as possible. Consumers demand cheap energy, energy producers want to produce the cheapest electricity to compete with their competitors, and governments want to minimize the energy bill for their constituents. The cost of generating electricity is an essential factor in determining the optimal generation mix.

Minimizing investment costs: Capital costs (CapEx)

The different costs involved in the construction and operation of an energy system can be split up to be able to better determine the desirability of a certain solution. Consumers most likely will not mind whether costs are capital costs, operational costs, or any other cost. For investors into RES-E projects, however, it is desirable to minimize the investment risk by lowering the capital cost of the investment.

Capital costs, or Capital Expenditure (CapEx), consider all costs that need to be done in the investment phase regarding the construction of the electricity plant and necessary transmission and other infrastructure. Investment costs for RES-E are bigger than for conventional generation (Hirth & Christoph, 2016). Investors into RES-E are, therefore, even more sensitive to risk than investors into conventional generation (Schmidt, 2014). Wentink (2019) also indicated that high investment costs pose a serious risk to investors and are a considerable barrier to the implementation of RES-E. Producers and cooperatives depend on investors to finance big energy projects, and high capital costs will significantly complicate the process of finding investors. Therefore, CapEx should be minimized.

Maximizing the returns on an investment: the Internal Rate of Return

Investors in energy projects want to maximize their returns and look at several different metrics to evaluate the attractiveness of an investment, apart from CapEx. The design of an energy system is a significant investment decision, and attracting investors is paramount to the successful integration of RES-E. Assessing the attractiveness of investment is often done by calculating the Internal Rate of Return (IRR). The IRR represents the discount rate at which the Net Present Value (NPV) would be zero.

The NPV for a project is calculated by discounting all life-time cash-flows of a project to their present value. A positive NPV indicates that the expected earnings exceed the expected costs even when the cash-flows are discounted for the time value of money. A high IRR means that the project is more attractive because it indicates high returns.

Although LCOE and IRR both represent different concepts, they are found to be perfectly (negatively) correlated. Intuitively this makes sense as well. As a producer, if you can produce electricity at a lower price, the profits will be higher, resulting in a higher rate of return for the investment. Because of the strong correlation with LCOE, IRR is not included as a separate criterion for comparing different generation mixes in this research: LCOE will be used. Although it is not used as a criterion to compare different compositions of the generation mix, investors will only invest in a project if it presents a return that is higher than the Required Rate of Return (RRR). Therefore, a generation mix can only be considered to be a feasible solution if the IRR is higher than the RRR.

The returns on an investment are just one side of the coin. The investors' choice on whether or not to invest in a particular project is the result of a consideration of the return on the investment and the (perceived) risk involved (Wüstenhagen & Menichetti, 2012). The risk of investment into RES-E depends on many contextual and behavioral factors (Wüstenhagen & Menichetti, 2012) and assessing the perceived risk involved in different energy portfolios is beyond the scope of this research. Risk of investment, together with several other criteria that are not incorporated in this research, is discussed further in appendix B. By considering LCOE, CapEx, and IRR, all the most relevant economic interests of the different actors from table 2.1 have been included. The next section evaluates the environmental considerations to take into account.

2.3.3. Environmental criteria: emissions in the energy system

The energy system has a significant impact on the environment by emitting large amounts of CO_2 and most actors are aligned in their objective to reduce this impact. In this research, because a regional energy system is considered, most CO_2 emissions are the result of importing ”grey” energy (generated mostly by conventional energy sources). Any energy generated within the region is generated from a renewable source and low on CO_2 emissions. Therefore, the emissions caused by the generation of imported energy should also be taken into account.

This research has set out to determine the optimal generation mix for different targets of reducing the emissions. Therefore, in this research, the reduction in emissions will not be used as a separate criterion to compare different designs, but as a condition that the system must be able to fulfill. It is taken to be fixed. Analyzing the generation mix for different targets of emission reduction is interesting not just from a research perspective, but also from a policy perspective. In reality, the emissions are not a point of discussion: most actors want to minimize the emissions. Instead, reducing emissions is a target that is set, and the solution should be optimally suited to reach this target.

Other researchers have used several environmental criteria, other than costs. These are not found to be relevant to this research and are discussed in more detail in appendix B. Several relevant social criteria will be discussed next.

2.3.4. Social criteria

The third category of criteria that will be discussed are the social impacts of energy systems. Social impacts are often hard to quantify and sometimes overlooked in modeling (Pasqualetti, 2011). In the introduction, several social barriers to the energy transition were already introduced, two of which are the acceptance of RES-E and the challenge of spatial integration of RES-E. A regional energy system that is only economically optimal may not be optimally suited to overcome these barriers. In this section, two criteria are introduced. Land use for energy production is introduced first.

Minimizing land used for energy generation

Section 1.2.2 introduced the challenge of spatial integration of RES-E: governments are having difficulties in finding available land for RES-E. The process of allocating land and changing destination plans is arduous and time-consuming and scares off investors (Wentink, 2019). Both wind turbines and solar panels take up more land than conventional electricity generation in large plants (Gagnon et al., 2002; Nonhebel, 2005). Therefore, a generation mix that requires significantly less land than another alternative, but performs comparably on other criteria will be more favorable: the process of allocating land and integrating RES-E into the environment will be easier and quicker. Available land is limited, and total land use for energy generation cannot exceed the available land.

Minimizing land use is also important to increase the acceptability of the energy system. Possible local resistance to the placement of RES-E is a significant risk to new investors and a barrier to the transition (Wentink, 2019). Local residents are impacted by the placement of RES-E near their house and other residents in the region may also have objections against RES-E being placed in the region. A lack of local acceptance can, therefore, be an issue when large amounts of land are required for energy generation (Busse & Siebert, 2018). Minimizing the land use for RES-E will decrease the number of people affected by RES-E, improve acceptability, and will lead to a faster energy transition.

Defining a measure for total land use is challenging. Wind turbines, solar panels, and biomass all use land in a different way: wind turbines are placed in wind farms, that span a certain surface, but farmers can still produce food around the turbines. Solar panels require much less land than other sources of renewable energy such as wind and biomass (Denholm & Margolis, 2008). Solar panels placed on roofs, do not use any land at all. Biomass uses land in the production of the biomass feedstock. The land use by the biomass plant itself, however, is relatively small. Some simplifications are necessary. In this research, therefore, the land use has been aggregated to one value of total land use in square kilometers.

The increased amount of land required to produce energy from RES-E is not the only issue leading to problems with local acceptance of RES-E. One of the main drivers for the lack of local acceptance is the perceived visual impact of wind turbines (Devine-wright, 2005; Krohn & Damborg, 1999). This is discussed next.

Minimizing the visual impacts of the energy system

Resistance against wind turbines in The Netherlands is a key barrier to the energy transition (Wentink, 2019). The perception of the visual impact of wind turbines is by far the most dominant factor in explaining the opposition against wind turbines (Wolsink, 2007). Many researchers in the social sciences field have investigated this (Devine-wright, 2005; Krohn & Damborg, 1999; Möller, 2006; Jobert et al., 2007). People may think that it negatively affects the landscape quality and perceive wind turbines to be 'ugly' (Wentink, 2019). The visual impact refers to the perceived negative effect on the quality of the landscape as a result of the placement of wind turbines. Large wind turbines lead to a higher visual impact than smaller wind turbines (Devine-wright, 2005). This negative effect on the landscape quality is an important point of discussion in The Netherlands, and dissatisfaction with the visual impact has even led to death threats being made to project developers (RTL.nl, 2019). Resistance from local residents can destroy the chances of completing construction of a wind or solar farm and can massively impact the lead-time of a renewable energy project (Wentink, 2019).

It would be interesting to see how much visual impact can be prevented without increasing costs or land use excessively. The visual impact of wind turbines is hard to quantify, and most studies use qualitative measures to evaluate the visual impact by ranking different alternatives (Antunes & Henriques, 2016). This study, however, makes a first attempt at quantifying the visual impact of wind turbines. The size of the area that is visually impacted by wind turbines is calculated and subsequently minimized. This approach is further explained in section 6.3.3.

It should be mentioned that not only the visual impact of wind turbines and land use influence local acceptance. Noise from wind turbines is often mentioned as a problem (Devine-wright, 2005). The level of annoyance from this noise is closely linked with the perception of the visual impact of the wind turbine (Pedersen et al., 2009). Several other factors such as how the turbines are aligned, the size of the wind park (Devine-wright, 2005), the perceived process justice (Wüstenhagen et al., 2007; Ellis, 2016) and the perceived distribution of costs and benefits (Wüstenhagen et al., 2007) are also important. There is much research that suggests that community ownership is an important step to increase the acceptance of RES-E (Slee, 2015; Ellis, 2016). Communities also want to be involved in decision making processes (Ellis, 2016). Other social factors that are relevant to some actors, such as increasing social cohesion through investing in RES-E projects and creating more jobs in the region, are not taken into account in this research. Success in creating jobs or increasing social cohesion depends on many contextual factors, and not as much on the composition of the generation mix. This is discussed in more detail in appendix B. After discussing all relevant social factors, technological criteria are considered next.

Table 2.3: Summary of the relevant criteria that will be used to assess the desirability of the design of a regional energy system.

Category	Criterion	Description
Economical		
	LCOE	The cost per generated kWh of electricity
	CapEx	Total Capital Expenditure (investment cost)
Environmental		
	-	-
Social		
	Land use	The total land required for energy generation in the region
	Visual impact	The area that is visually impacted by wind turbines
Technological		
	-	-

2.3.5. Technological criteria

An energy system is a technological system, and many different technical considerations come into play. No technological criteria, however, are found to be relevant to this research.

Reliability of supply is a very important consideration to most actors. The reliability of the energy supply is a measure of how reliably the system can fulfill demand. This research analyzes the generation mix for a grid-connected system, as explained in section 1.4.2. In a grid-connected system, the reliability of the electricity supply is guaranteed by a connection to the central grid, so evaluating the reliability is not relevant.

The system operators (TSO and DSO) are responsible for balancing supply and demand and are interested in the peak-load response of the energy system. This is a measure of how well the system is able to cope with sudden peaks in demand. Because, in this research, the peak-load response is guaranteed by a connection to the grid, this criterion is also not taken into account. All technological criteria found in literature, including reliability and peak-load response, are included in appendix B.

2.3.6. Summary of criteria selection: four criteria will be used in this research

A summary of the four most relevant considered criteria is provided in table 2.3. These four criteria are used in this research to assess the desirability of a generation mix, given a certain amount of CO_2 reduction. Finding a generation mix that performs optimally regarding these four criteria is the main goal of this research. In the sections above, it is explained that minimizing LCOE is essential to safeguard the affordability of electricity. Minimizing CapEx is essential for producers and energy cooperatives in order to be able to attract investors. Land use and visual impact are important criteria to analyze the social impacts of the generation mix. Spatial integration of RES-E is a big challenge in The Netherlands and an energy system that minimizes land requirements is more suitable for real-world implementation. The visual impact should also be minimized. The visual impact of wind turbines is a big point of discussion and the main determinant for the social acceptability of the energy system.

Two other important factors that are identified from examining the interests of the involved actors are discussed above, but will not be used to assess the desirability of a generation mix. Minimizing CO_2 emissions is important to most actors. This research, however, will focus on finding the optimal generation mix given a certain reduction in CO_2 emissions. The reduction in emissions is taken to be fixed and not used to find the optimal generation mix.

The return on investment, measured by the IRR, is also not included as a separate criterion. IRR is strongly correlated with LCOE, as explained in section 2.3.2. The LCOE is used to compare the attractiveness of investing in different sets of technologies: cheaper energy generation means a higher return.

Having identified the four criteria, the most important interests of the actors from table 2.1 are included in this research and the barriers discussed in the introduction have been extensively considered. The final step is to align the actors with the criteria that are included in this research.

Table 2.4: Evaluating the preferences of the actors on the criteria that are included in this research.

	LCOE	CapEx	Land use	Visual impact
Min/max	min	min	min	min
National gov't	√		√	√
Provincial gov't	√		√	√
Municipal gov't	√		√	√
Producers	√	√		
Consumers	√			
Local residents against RES				√
Cooperatives	√	√		
Land owners	√		√	√
TSO				
DSO				

2.4. Aligning the most relevant criteria with the involved actors

Now that the most important actors and the most relevant criteria have been identified, the next step is to evaluate which of these criteria are important to which actors. The interests of the actors were summarized in table 2.2. Table 2.4 provides an overview of the interests of the actors regarding the four selected criteria.

Firstly, most actors intend to minimize LCOE. Either from a consumer perspective (cheaper energy means less costs) or from a producers perspective (cheaper production of energy means a higher IRR and a better competitive position). Minimizing LCOE is also very important to all levels of government, since guaranteeing the affordability of energy supply is one of their main targets.

Only the producers and cooperatives are interested in minimizing capital expenditure. Minimizing capital expenditure means that fewer investors are needed and the solution is less risky and more attainable. The other stakeholders are not concerned with minimizing CapEx.

Land use by RES-E is a main concern of all governments. They know the challenges involved in allocating land. The consumers are assumed not to be concerned by the land used for the electricity that they buy from producers; they only care about the price.

Minimizing visual impact is also important. The local residents want to prevent any visual impact by RES-E in their region and this is their only interest. Governments want to minimize visual impacts for their constituents and land owners want to minimize the impact close to their houses.

It is clear from this table that the DSO and TSO do not have any specific interests regarding the criteria that are included in this research. This is a result of the choice to exclude energy transmission and the guaranteed flexibility through a connection to the national grid. The TSO and DSO are responsible for energy transmission and guaranteeing the reliability of supply (see appendix B). Because the TSO and DSO are not directly interested in any of the relevant criteria, they will be left out of further analysis. Although not relevant in this analysis, the TSO and DSO are the main responsible parties regarding the installation of the energy transmission infrastructure, and they should be involved throughout every step in energy systems planning.

2.4.1. Grouping several aligned actors

From table 2.4, it is clear that several actors are aligned regarding the four criteria. The aligned actors can be aggregated to four actor groups to simplify the analysis: governments, investors, consumers, and local residents. This aggregation of actors is now discussed.

All levels of government are aligned in their interest to minimize LCOE, land use, and visual impact. Governments make up the first composite actor. The land owners have identical interests to the governments. Therefore, they are also represented by the governments.

The producers and energy cooperatives are only concerned with minimizing CapEx to be able to fund projects and minimizing LCOE to maximize profits. The producers and cooperatives also make up one actor group: the investors.

The local residents that want to prevent visual impact from RES-E are unique in their

Table 2.5: Evaluating the interests of the four main actor groups regarding the criteria that are included in this research.

	LCOE	CapEx	Land use	Visual impact
Min/max	min	min	min	min
Governments	√		√	√
Investors	√	√		
Local residents				√
Consumers	√			

interests: they only care about minimizing the visual impact. Because of their unique focus, local residents organizing against RES-E are also included an actor group.

Consumers are a critical actor. By deciding where to buy their electricity from, they shape the development of the energy system. Consumers make up the final actor group: they are only concerned with minimizing the price of electricity. They buy electricity where it is the cheapest (if emissions are taken to be fixed).

By identifying these four actor groups, all critical actors and interests are represented. Therefore, it is concluded that this categorization is a valid representation of the actor landscape regarding this problem. The preferences of the four actor groups are shown in table 2.5.

2.5. Conclusion

In this chapter, the actors in the energy system, and four criteria to take into account when designing a regional energy system are identified. Finding a generation mix that performs best on these four aspects will be the main focus of this research. The priorities of the stakeholders involved have been mapped. From this analysis, it is clear that four actor groups can be identified, which will be used in the remainder of this research.

Which generation mix best satisfies all demands from the different actors is not directly clear. A model is needed to answer this question. The next chapter will set out to provide a review of the relevant literature to find knowledge to build on and will identify a clear research gap that this research will fill.

3

Current state of energy systems modeling and relevant literature

To gain insight into the optimal design of a regional energy system, a model is needed. Multiple objectives need to be considered, and the amount of parameters is too large to find an optimum by hand. Modeling the energy system will lead to more insight into the functioning of the system and the trade-offs to be made.

The modeling of energy systems is a field of study that is already well developed. Therefore, this research can use previous research to build on the work that has already been done in the field of energy systems modeling.

Many different types of models exist to analyze the energy systems. This chapter sets out to identify the most important concepts and to discuss the most relevant developments in the field of energy systems optimizations. First, an overview of the different types of models is provided before optimization models are investigated in more detail.

3.1. Categorization of energy system models

Jägemann et al. (2013) identify two main types of models: macro-economic models and power sector models. In macro-economic modeling, the energy system is evaluated as a part of the entire economy. The effects of one sector on another are evaluated. Macro-economic models are characterized by a low level of technological detail. This research will not use a macro-economic approach. Instead, a power sector model is used. Power sector models focus only on the energy system and usually employ a higher level of technological detail. Within the area of power sector models, two main types can be distinguished: bottom-up simulation models and top-down optimization models.

In bottom-up simulation models, analysis is done by evaluating the results of individual decisions. Methods such as agent-based modeling or system dynamics modeling are used.

Top-down optimization models assume a central planner and aim to find the optimal design of the energy system. In this research, to find the optimal design of the energy system, a top-down optimization model is used. This chapter will further investigate the field of energy systems optimization models. First, a differentiation based on the objectives included in the optimization will be made. After this, different methods of solving the optimization will be discussed. In section 3.4, some of the most relevant studies are discussed.

3.2. Single- vs. multi-objective optimization

The selection of objectives for an optimization has a big impact on the outcome. Most studies on energy systems optimizations focus on optimizing for a single objective. The vast majority of studies optimize for cost as a single objective (Theo et al., 2017). To find the optimal design for a stand-alone energy system, reliability is also often used as a single objective (Al-falahi et al., 2017). Reliability is usually defined as the ability of the energy system to fulfill demand at all times (Diaf et al., 2007; Maleki & Pourfayaz, 2015).

Most studies optimize the energy system to ensure minimal cost. However, in a complex socio-technical system, optimizing purely for cost is a narrow view of the challenge. There is a trade-off between the different objectives, such as cost and reliability. Therefore, researchers have tried performing multi-objective optimizations to try and get a more complete picture of what the optimal socio-technical design would be. Alarcon-Rodriguez et al. (2010) identifies two ways of incorporating multiple objectives in the optimization problem.

Firstly, the different objectives can be merged into a single objective function: so-called scalarization of the objective function. One optimal solution will be found, similar to a single-objective optimization. Secondly, one can search for a set of Pareto-optimal solutions for all objectives. This will result in a set of optimal solutions on the Pareto-frontier (Chinchuluun & Pardalos, 2007). The Pareto-optimal set of solutions is the set of non-dominated solutions of the multi-objective optimization. A solution is not dominated by any other solution if there does not exist another solution which is better regarding each objective. Having made the distinction between single- and multi-objective optimization and having introduced the concepts of scalarization and pareto-optimality, some methods used to solve optimization problems will now be introduced.

3.3. Energy system optimization models: typical optimization methods

In the previous section, the scope of an energy system optimization model was defined, and different types of optimizations are introduced. Optimization problems can be solved in different ways. Siddaiah & Saini (2016) and Sinha & Chandel (2015) identify three categories of optimization methodologies. 1. Mathematical techniques, 2. Artificial intelligence techniques and 3. Hybrid techniques

Which technique is most suitable depends on the application and the user's preferences. There have been many studies comparing the optimization methods and their respective efficiency and usefulness such as Baños et al. (2011) and Al-falahi et al. (2017). The three categories of optimization techniques will now be shortly discussed.

Mathematical techniques, such as linear programming (Wang et al., 2019; Omu et al., 2013; Cormio et al., 2003; De Pater, 2016; Haikarainen et al., 2019), non-linear programming or multi-objective programming, are analytical in nature. They are useful if the model uses continuous functions with an analytically determinable global minimum (Siddaiah & Saini, 2016). Mathematical methods are relatively quick and straightforward to use.

Artificial Intelligence (AI) techniques apply intelligent algorithms to find optimal solutions for problems where an analytical solution is not easily found (Siddaiah & Saini, 2016). Examples of AI techniques are genetic algorithms and Particle Swarm Optimization. Baños et al. (2011) provide an overview of AI techniques. Evolutionary optimization methods, such as genetic algorithms, have been shown to work quite well in multi-objective optimizations (Oree et al., 2017). They can search for several Pareto optimal solutions simultaneously and are also able to solve discontinuous problems. There has been a significant development in the area of multi-objective evolutionary optimization. The most well-known evolutionary optimization algorithm that has proven to be quite effective is the so-called NGSA-II algorithm (Deb et al., 2002; Baños et al., 2011; Al-falahi et al., 2017). Artificial intelligence methods can be quite complex and require multiple iterations before a solution is found.

Hybrid techniques employ a combination of two or more algorithms. These can be used to overcome the limitations of one specific technique (Upadhyay & Sharma, 2014). These hybrid techniques, however, can quickly become very complex and computationally expensive.

3.3.1. Energy systems optimization tools

In addition to the many studies that develop, or adapt from literature, their own model, there is a large stream of literature using existing energy systems simulation models that have been developed by different institutions. An overview of existing modelling tools can be found in Connolly et al. (2010) and Allegrini et al. (2015) and Ma et al. (2018). Every model has its own characteristics regarding included energy resources, optimization objectives, optimization methodology, and scale. Hori et al. (2016) identify four models that can be used on a regional scale: MODEST, energyPRO, HOMER, and ETEM. Most simulation models include both electrical energy and heat energy. All these four simulation models, optimize for a cost-optimal solution. Modeling tools offer black box coding and often have a higher computational time (Singh et al., 2016). This research includes several other newly defined criteria. A high degree of flexibility and customizability is necessary, and none of the simulation tools perfectly fit this research. This research will, therefore, not use a modeling tool. The next section identifies the most relevant studies in the field of energy systems optimization.

3.4. Relevant optimization studies in the field of energy systems modeling

This research will include multiple criteria in the optimization. In literature, however, most studies mainly focus on one objective. First, some studies using only one objective are discussed. Table 3.1 provides an overview of the discussed studies.

3.4.1. Single-objective optimization studies

Single-objective energy systems optimizations usually aim to find either an economic optimum (cheapest) or the technological optimum (minimal exports). Each study has a specific focus. Brouwer et al. (2014) investigated the cost optimum for a European power system. It is found that high penetrations of RES-E lead to significantly higher system cost. It is concluded that demand response and increased interconnection capacity can reduce the system cost. Heide et al. (2010) investigated a technological optimum for minimal energy mismatch for the European energy system for a 100% renewable situation. They found a mix of 55% wind and 45% solar to be the technological optimum. Yang et al. (2007) investigated the cost-optimal battery size for a stand-alone energy system for different reliability demands. In a study by Rodriguez et al. (2015), two different optimal solutions were compared. First, a technological optimum was found by minimizing the required back-up capacities. This solution was compared with a cost-optimal system. They found that, although it is not the technological optimum, a share of 94% wind power was the cost-optimal solution. Diaf et al. (2007) studied a stand-alone hybrid energy system and concluded that at 100% reliability, over 30% of the generated energy is wasted unless unrealistically high amounts of storage are included. Ouedraogo et al. (2015) looked into the effects of the discount rate on the optimal PV and diesel generator mix for a stand-alone hybrid energy system for a village in Burkina Faso. They found that investment costs are high for PV, and a high discount rate serves as a barrier to high RES-E penetration. All studies discussed above use one objective. Several studies using multiple objectives are also relevant to this research. Earlier in this research, it was concluded that the energy system is a complex socio-technical system. Therefore, some studies that also use some more social objectives (instead of economical and technological) will also be considered.

3.4.2. Multi-objective optimization studies

Several multi-objective studies are now introduced with a specific focus on the objectives that were included. Moura & de Almeida (2010) defined objectives for minimal intermittency, both monthly and yearly, and minimal cost. They scalarized the objective function for two objectives: minimal intermittency and minimal cost. Stochastic climate data was used. They found that by minimizing the intermittency, the required overcapacity can be reduced by 30%. Abbes et al. (2014) used a variant of the NSGA-II algorithm to find the Pareto optimal set of results for a stand-alone energy model of a household. LCOE and reliability were included as objectives, combined with a measure for the primary energy which is used in the production of the wind turbines, batteries, and solar panels to optimize the sustainability of the energy system. Bernal-agustin et al. (2006) performed a multi-objective optimization

Table 3.1: Overview of the discussed papers. SOO = Single-Objective Optimization, MOO = Multi-Objective Optimization, MOO-SC = Multi-Objective Optimization Scalarized, LCOE = Levelized Cost of Electricity, TAC = Total Annual Cost, HDI = Human Development Index, LPSP = Loss of Power Supply Probability (reliability), PM = Particulate matter, EE = Embodied Energy, NPC = Net Present Cost, LCC = Life-Cycle Cost, WRE = Wasted Renewable Energy, LP = Linear Programming, MIP = Mixed Integer Programming, GA = Genetic Algorithm, PSO = Particle Swarm Optimization, BFPSO = Bacterial Foraging PSO, TLBO = Teaching-Learning Based Optimization, SPEA = Strength Pareto Evolutionary Algorithm, MOLP = Multi-Objective Linear Programming, DG = Diesel Generator, ES = Energy Storage, HP = Hydro Power, BM = Biomass, CG = Conventional Generation, EC = Energy Conversion

Research	SOO/MOO	Objectives	Optimization method	GC/SA	Scenario	Time-scale/resolution	System size	Elements
Ouedraogo et al. (2015)	SOO	LCOE	HOMER	SA	Impact of changing discount rate on LCOE	Year/hourly	Village in Burkina Faso	PV, DG
Yang et al. (2007)	SOO	LCOE	Iterative	SA	Several scenarios of minimal reliability	Year/hourly	Unspecified	Wind, PV, ES
Heide et al. (2010)	SOO	Minimal energy mismatch	LP	GC	100% renewable	6 weeks per year for 8 years/ hourly	Europe	Wind, PV
Brouwer et al. (2014)	SOO	TAC	MIP	GC	3 RES-E penetration scenarios	600 periods per year	Europe	Wind, PV, BM, HP
Rodriguez et al. (2015)	SOO	LCOE	LP	GC	Cost vs. Technologically optimal	8 hours/hourly	Europe	Wind, PV
Diaf et al. (2007)	SOO	LCOE	Iterative	SA	Different reliability scenarios	Year/hourly	Corsica island	Wind, PV, ES
Moura & de Almeida (2010)	MOO-SC	Minimal intermittency, TAC	LP	GC	Increasing renewable shares over the years	Year/hourly	Country (Portugal)	Wind, PV, HP
Sawle et al. (2018)	MOO-SC	HDI, LPSP, LCOE, PM	GA, PSO, BFPSO, TLBO	SA	5 compositions of the generation mix	4 typical days/hourly	District in India	Wind, PV, BM, DG
Abbes et al. (2014) 2014	MOO	LCOE, LPSP, EE	GA (NSGA-II)	SA	-	Month/half-hour	Household	Wind, PV, ES, EC
Bernal-agustin et al. (2006)	MOO	NPC, CO_2	SPEA	SA	-	Day/hourly	Farm	Wind, PV, ES, DG, EC
Gabrielli et al. (2018) 2018	MOO	CO_2, TAC	MILP	GC	-	Year/hourly	Neighbourhood in Zurich	CG, PV, BM
Fazlollahi et al. (2012)	MOO	CO_2, TAC	GA	GC	-	year/hourlt	Unspecified	CG, PV, Wind, BM
Di Somma et al. (2018)	MOO	LCOE, CO_2	LP	GC	-	Day/hourly	Household	PV
Ogunjuyigbe et al. (2016)	MOO	LCC, CO_2, WRE	GA	SA	4 compositions of the generation mix	10 days/ hourly	Household	Wind, PV, DG, ES
Arnette & Zobel (2012)	MOO	LCOE, CO_2	MOLP	GC	Minimal cost at different RES-E penetration levels	Year/hourly	Large region in the US	Wind, PV, BM
Perera et al. (2013)	MOO	LCOE, WRE, LPSP, Fuel consumption	GA	SA	-	Year/hourly	Village in Sri-Lanka	Wind, PV, DG

minimizing the CO_2 emissions and the Net Present Cost. They used an evolutionary multi-objective optimization algorithm (SPEA) to find the Pareto-optimal set of solutions. The solutions (a Pareto-front for emissions and cost) was not further analyzed, and the decision on the ideal generation mix was left to the reader. Gabrielli et al. (2018) optimized for total annual cost and annual CO_2 emissions using mixed-integer linear programming to investigate the role of seasonal storage in a future energy system. They visualized Pareto-front to analyze the set of solutions. They applied their model to a specific neighborhood in Zurich, Switzerland. They determined that if emissions are reduced by more than 90%, seasonal storage becomes an attractive option. Fazlollahi et al. (2012) created a non-linear multi-objective model which they solved using several different methods. A multi-objective genetic algorithm proved to be the most effective but did take the most computing power to solve. They analyzed the effectiveness of the algorithms using a Pareto-front for the objectives of cost minimization and CO_2 emissions minimization. Di Somma et al. (2018) used a linear programming model to determine the optimal solution based on daily energy price and daily CO_2 emissions. A Pareto-front is used to determine which solutions are optimal. An interesting contribution of this paper is the inclusion of both supply- and demand-side uncertainties. The model is applied to a building in Italy. Ogunjuyigbe et al. (2016) consider a stand-alone system mainly based on RES. They also include diesel generators in their model to fill up the demand if the RES cannot fulfill it. They perform a tri-objective optimization minimizing LCC, emissions, and surplus energy. The optimization is done using a genetic algorithm, and a typical household is used as a case study to validate the model. As their optimal solution, they take the solution for when the genetic algorithm stops converging. The result is a non-dominated solution. There are, however, also other non-dominated solutions. How they choose the single optimal solution is not specified. A small remote district in India was analyzed by Sawle et al. (2018), considering RES and diesel energy generation. They used six objectives combined into one composite goal function. Several different optimization methods and five different compositions of the generation mix are compared. They found that a specific artificial intelligence algorithm called the teacher learning based optimization algorithm performed best. Common objectives, such as the Cost of Energy, reliability, and renewable percentage are included. There are, however, also social factors such as the human development index and job creation included in the model. There can be some discussion about the way that these have been included. For instance, the authors argue that excess electricity generated will benefit the Human Development Index (HDI) in this region. This is based on the study by Dufo-lopez et al. (2016), who applied this HDI objective as part of a tri-objective optimization for a refugee camp in Algeria. They use a multi-objective evolutionary algorithm to find the solution, also considering only RES and diesel generation. So far, none of the discussed studies have looked into the challenges of land use and visual impact from RES-E. A study which did incorporate land use, but only as a constraint, is the study by Arnette & Zobel (2012), which optimized an energy system in the US to investigate the minimal cost at different levels of emission reduction. Finally, Perera et al. (2013) performed an interesting study where a stand-alone energy system for a village in Sri-Lanka is optimized for four objectives (cost, reliability, wasted renewable energy, and fuel consumption). To analyze the Pareto front, Multi-Criteria decision making is performed for these four criteria (see also section 3.5.1).

3.5. Multi-Criteria Decision Making in energy systems planning

Another direction of literature explains the process of Multi-Criteria Decision Making (MCDM). MCDM deals with decision problems under several decision criteria (Hussain Mirjat et al., 2018). MCDM is not an optimization method. It starts with a set of possible solutions and the performance of these solutions on all criteria. MCDM is subsequently applied to rank the solutions or to find the single most desirable solution. Different methods for coming up with a ranking or optimal solution exist. An extensive review of the most applied methods can be found in (Pohekar & Ramachandran, 2004). An example of MCDM applied to find the optimal energy generation mix is the study done by Hussain Mirjat et al. (2018). They use an optimization model to find cost-optimal solutions for four different policy-scenarios. MCDM is consequently applied to compare and contrast the different scenarios. Most studies such as Streimikiene et al. (2012), however, do not compare optimization outcomes but compare different energy sources based on their relative desirability. An interesting note about these MCDM decision making methods, is that they allow the modeler to include qualitative factors in the decision, apart from just quantitative factors.

3.5.1. Using MCDM to process optimization results

As can be seen from the studies mentioned above, multi-objective optimization results in a Pareto-front: a set of optimal solutions. These optimal solutions could subsequently be ranked using MCDM techniques. This has been applied in other fields such as structural or logistical engineering (Selmi et al., 2016; Wismans et al., 2014). In energy systems optimization, this technique has also been applied. Two studies were found applying this method: Soroudi et al. (2011) has used an innovative genetic algorithm inspired by human immune system mechanisms. They optimize for emissions and cost. After determining a set of solutions on the Pareto-front, they subsequently use a fuzzy decision-making method (Sakawa & Yano, 1989) to select the best alternative. The study by Perera et al. (2013), mentioned above, also uses MCDM to find the final optimal solution for cost, reliability, wasted renewable energy, and fuel consumption. No studies within the field of energy system optimization, however, have compared ideal situations for different stakeholders to reflect on the Pareto-front. The previous chapter shows that this indeed would be relevant since the preferred situation differs for each stakeholder.

3.6. Conclusions from the literature review and knowledge gap

From the optimization studies mentioned above, it is clear that minimizing land use and minimizing the visual impact in an optimization has not yet been done. Multi-objective optimization for energy systems is a topic which is well researched, but the main focus in literature is optimizing an energy system for reliability, cost, or emissions. Although many studies (Denholm & Margolis, 2008; Palmer-wilson et al., 2019; Nonhebel, 2003; Arnette & Zobel, 2012) indicated that land use by RES-E is a significant issue, it has not been included as a separate objective. The same is true for research into the visual impact of wind turbines (Devine-wright, 2005; Krohn & Damborg, 1999; Möller, 2006; Jobert et al., 2007). No efforts have been made to incorporate these challenges into a multi-objective optimization model: there is a big gap between social studies researching land use and local acceptance, and energy systems optimization studies.

Keles et al. (2017) notes that, although a cost-optimum is the theoretically ideal solution, real-world projects will often face delays due to public acceptance and the real-world solution may shift to a more expensive solution than the theoretically ideal solution. Al-falahi et al. (2017) also states: "few studies have considered social assessments such as human development, job creation, and social acceptance in optimization problems. (...) Considering these factors in size optimization problems is recommended." This research attempts to bridge this gap. Also, no researchers have yet taken a multi-actor perspective to the energy system optimization. Perera et al. (2013) has shown that using MCDM to process the results of multi-objective optimization is possible. Perera et al. (2013), however, does not consider the results from a multi-actor perspective. This research will use MCDM from a multi-actor perspective to further analyze the Pareto-front that results from the optimization.

This concludes the literature review. The most important contributions of this study can be summarized into two main points. Firstly, this study will bridge the gap between energy system optimization studies and studies into land use and visual impact by including these as separate objectives. Secondly, this study will present an innovative way to combine the field of multi-objective optimization and the field of MCDM studies by processing the results of the optimization using MCDM. The next chapter will introduce the model that is used.

4

Description of the simulation model

In order to answer the research question, an optimization model of a regional energy system has been constructed. This chapter will discuss the formal structure of the model. The model consists of 2 main parts: a simulation part and an optimization part. This chapter will provide a complete formulation of the simulation model. The next chapter will describe the optimization that is performed using this simulation model. After the optimization has been detailed, chapter 6 will expand on the specific data inputs and verify the behavior of the model. This chapter will first discuss the high-over structure of the model. After the structure has been discussed, the simulation model is defined.

4.1. High-over structure of the energy system optimization model

The structure of the model has been represented in figure 4.1. This figure will now be explained, starting from the simulation model of the regional energy system.

The simulation model (number 2 in figure 4.1) simulates a year of energy production and consumption in the region given a certain data input (number 1 in figure 4.1) and the values of the decision variables (number 4 in figure 4.1). The data input is identical for each simulation and consists of information such as the demand profile and the cost of different technologies. The decision variables are chosen by the optimization algorithm (number 5 in figure 4.1) and will be different for each run. The decision variables consist of the installed capacity of different technologies. The simulation model generates several outputs (number 3 in figure 4.1), such as total cost and total land use with the given generation mix. These outputs are passed back to the optimization algorithm. The optimization algorithm subsequently evaluates the outputs and chooses new values for the decision variables based on previous iterations in order to improve on the objectives.

The simulation model is run again with these new decision variables and passes the new outputs to the optimization algorithm. This process is repeated until the optimization algorithm reaches the stopping criterion. At this point, the optimization algorithm will output

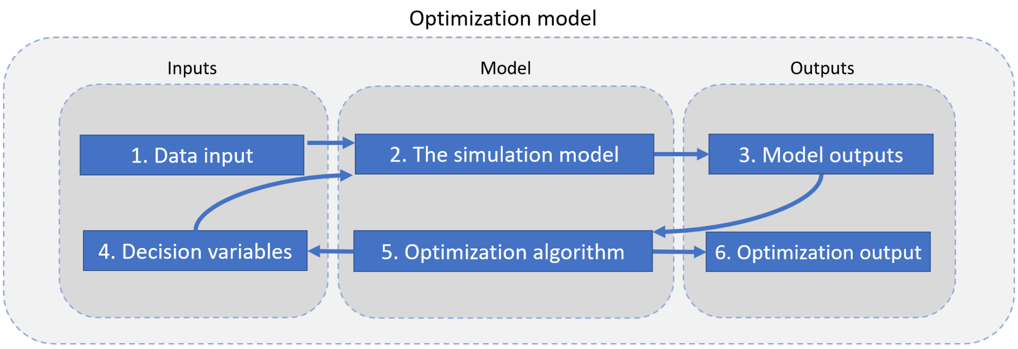

Figure 4.1: Visualization of the high-over structure of the energy system optimization model

the results of the optimization (number 6 in figure 4.1). The output of the optimization model consists of a set of decision variables that were best able to minimize the objectives given the constraints. The simulation model used to generate the outputs will be discussed in more detail in this chapter.

4.2. Description of the simulation model and data inputs

The simulation model is an integral part of the total optimization model. It calculates several outputs such as LCOE and emissions based on a given generation mix. Installed capacities of different technologies are used as input for the simulation model. The simulation model must represent reality as much as possible in order for the results to be meaningful. The complexity of any model, however, can be increased infinitely and some choices in determining the scope of the model need to made to keep the model manageable. The next section will explain the choices that are made in determining the scope of the model.

4.2.1. Scope of the simulation model

This section describes the boundaries of the model and some of the assumptions that are made. Several aspects of the scope will be discussed. The first is the time horizon and the resolution of the model.

Time horizon and resolution

The time horizon and the resolution of the model should be chosen so that all relevant effects are taken into account while keeping computation time to a minimum. The simulation model simulates a full year of production and demand. This is to ensure that all daily, weekly, and seasonal effects are taken into account. Taking a time horizon of one year means that effects such as declining performance of RES-E are not taken into account. A resolution of one hour was chosen. Most effects of the intermittency of RES-E are because of an hourly variation in production. Therefore, if a lower resolution is taken, these effects cannot be captured. Hourly data is also widely available. The hourly resolution requires the assumption that demand and production are constant for every hour and neglects effects that are only noticeable on a shorter term.

Number of nodes

An energy system model can consist of multiple nodes: locations of production and consumption. This research only considers one node. Two main assumptions are made by modeling the system as one node. The first assumption is that the weather is identical throughout the region. No major differences in the production of RES-E are to be expected within a relatively small region, so this is an acceptable assumption. The second assumption is that all electricity is generated at the location where the demand is: no transmission network is included. Not including the network leads to a less realistic design, but it is an acceptable assumption because the distances within a region are relatively small. This will likely not influence the total composition of the generation mix.

Inputs and outputs

The simulation model requires two main sources of input. First of all, the installed capacities of the different technologies are required. Secondly, the model requires data input. This data input consists of hourly data on solar irradiation, wind speeds, and energy prices. Also, the costs of different technologies, parameters regarding land use and visual impact are required. The data used in the model is specified in chapter 6. The model evaluates the functioning of the energy system, given the installed capacities, and provides several outputs. The outputs have been defined in chapter 2.3 and formulas for the outputs will be provided below.

Elements of the energy system included

An essential part of the scope of an energy system model are the elements of the energy system that are included. The energy system consists of energy production, transmission, energy storage, and energy consumption (demand). All energy system models include some energy demand. In this case, the energy demand of one region. Several methods of production have been included, which will be discussed in section 4.2.2. Energy storage has also been considered in the model as a means to balance demand and supply. The methods of storage will be discussed in section 4.2.3. Energy transmission, however, has not been considered in the model. This choice has been made because a relatively small region is considered were transmission losses will be relatively small because of the small distances. Energy conversion has also been left out of the scope of this research. The included generation methods are discussed next.

4.2.2. Choice in generation methods

Which generation technologies are considered is an important modeling choice. All relevant generation methods should be included. This research does not consider methods that are not realistic for a region to invest in locally. This excludes conventional generation methods such as nuclear energy, coal-, and gas-fired power plants. These generation methods benefit from economies of scale and are not profitable on a small regional scale.

Wind energy, and solar PV are included in the model. These are currently the most widely applied RES-E and are expected to have a large contribution to the generation mix in the future. Most studies consider wind and solar energy to be of one standard type. In this research, the choice is made to split up solar energy and wind energy into different types. These different types have distinct properties that may yield some interesting insights.

Solar energy is split up into utility-scale solar and residential solar. Utility-scale solar has a capital cost that is significantly lower than residential solar. Residential solar, however, can be placed on rooftops and does not require any land. Also, utility-scale solar has a higher operational cost due to the renting of the land. Residential solar and utility-scale solar yield the same amount of energy per panel. An assumption is made that all solar panels are oriented towards the south with a typical angle of 35 degrees.

Wind energy is a cheaper method of generating renewable energy than solar energy. In this research, wind energy is split up into two different types of turbines with different sizes. Turbines with different sizes also have some different properties. The bigger turbine does not only have a higher rated power, leading to more output at the same wind speed; it also has a higher tower. Wind speeds at higher altitudes are significantly higher, leading to even higher output at the same (ground) wind speed. Bigger wind turbines, however, need to be placed further apart. More land is needed for a wind farm of identical size. A smaller wind turbine will use less land and will also cause less visual impact. In this research, a relatively small wind turbine (Vestas V66) with a rotor diameter of 66 meters and a rated output of 1750kW is used. The big turbine has a rotor diameter of 110 meters, which is relatively big for an onshore turbine. In the model, a Vestas V110 with a rated output of 2MW is used.

Solar and wind energy are the most promising RES-E. Other sources of renewable energy such as tidal energy are quite far from being economically attractive (Chu & Majumdar, 2012). Hydropower is already quite developed and economically attractive. In this research, hydropower is not included. The possibility of implementing hydropower depends mainly on geographical factors. Modeling rainfall and the melting of snow for hydropower would impose some severe challenges. For a region in The Netherlands, hydropower is not the most promising solution. In Scandinavia or the Alps, however, one should consider including hydropower in the optimization. Off-shore wind energy has also been left out of the scope of this research. Constructing an off-shore wind farm is not a decision that one region would be able to take by itself. It would require national coordination.

Some flexible generation capacity is necessary to fulfill demand when wind speeds and solar irradiation are low, or there is a peak in demand. **Energy from biomass** is a source of renewable energy that can be used as backup capacity. Biomass energy has a relatively low capital cost, but a high operating cost because it burns fuel. Biomass plants can be fed by different types of feedstock. This research assumes that the feedstock is made up of energy crops such as grasses or trees grown in the region.

In the model, wind and solar power are dispatched whenever available because there are no additional costs associated with generating electricity. Biomass energy is only deployed when necessary. Energy storage, described below, is also used to fulfill demand. If there is still a shortage, energy can be imported from the main grid.
To summarize: 5 different methods of generation will be included in the optimization.

- Residential solar has a relatively high capital cost but does not require any land for energy generation.
- Utility-scale solar is slightly cheaper than residential solar but does require some land.
- Vestas V110 wind turbines are big wind turbines that produce cheap renewable energy, but require a large amount of land and have a large visual impact.
- Vestas V66 Small wind turbines produce more energy per euro than solar panels but significantly less than the V110 wind turbine. They have a smaller visual impact and land use than larger wind turbines.
- Energy from biomass uses fuel, incurring costs when generating energy but is a more flexible means of generating energy.

The technologies have now been described, the specific characteristics per technology will be discussed in chapter 6.

4.2.3. Storage methods

Several solutions exist to store electrical energy. They can be split up into two groups: short-term and longer-term storage. Examples of storage methods for short term storage are lithium-ion batteries, flywheels and flow batteries. If energy is stored for a longer term, it can be stored as potential energy by pumped hydro storage or as chemical energy in hydrogen. Short term energy storage has a relatively high cost for installing storage capacity, but low cost per kWh that is stored. For longer term storage, this is the other way around.

In this research, due to scope considerations, only short term storage is included. The intermittency of RES-E is a short term effect, and when considering high degrees of self-sufficiency, some energy storage may be desirable to be able to fulfill demand when supply is low. Long term storage is left out of the scope of this research. Long term storage, however, may be relevant for future energy systems to be charged in the summer and discharged in the winter.

4.3. Mathematical formulation of the simulation model

The scope of the model has now been defined. The mathematical formulation of the simulation model is provided below. Table 4.1 shows all sets, parameters, and variables used in the formulas below.

4.3.1. Defining the sets

To allow for clear notation, several sets are identified, which are discussed now.

The model is run for one year with an hourly resolution. Therefore, there are 8760 time-steps evaluated in the simulation model. The time step is denoted by $t(\in T = \{1, ..., 8760\})$.

The different technologies have also been grouped into sets. Three sets are defined. First, I is defined to be all solar and wind technologies. Two types of solar (rooftop-mounted and utility-scale), as well as two types of wind power (V66 and V110 turbines), are included.

Secondly, G is the set of all technologies that generate electricity. This includes wind, solar, and biomass.

Thirdly, A is defined as the set of all technologies. This includes wind, solar, biomass, and also energy storage. Having defined these sets, the next section will introduce the energy generation from solar and wind.

Table 4.1: Overview of all sets, parameters and variables used in the simulation model

	Sets	
Notation	*Description and range*	
I	Set of the intermittent sources of energy (wind (2 types) and solar (2 types))	
G	Set of all energy generation technologies (wind (2 types), solar (2 types), biomass)	
A	Set of all considered technologies (wind (2 types), solar (2 types), biomass, storage)	
T	Set of all time steps, {1,...,8760}	
	Parameters	
Notation	*Description*	*Unit*
$\mathrm{ED}(t)$	Energy demand at time t (t∈T)	kWh
$\mathrm{CF_i}(t)$	Capacity factor of technology i at time t (i∈I, t∈T)	kW/kW
tau	Size of a time step (1 hour)	h
$\mathrm{EP}(t)$	Price of importing energy at time t (t∈T)	€/kWh
$\mathrm{VC_i}$	The variable costs of technology i (i∈G)	€/kWh
$\mathrm{FC_i}$	The fixed costs of technology i (i∈G)	€/kW
$\mathrm{VC_{storage}}$	The variable costs of storage	€/mWh
$\mathrm{FC_{storage}}$	The fixed costs of storage	€/mWh
η	Efficiency of energy conversion for storage	kWh/kWh
κ_i	Investment costs for technology i (i∈G)	€/kW
κ_storage	Investment costs for storage	€/kWh
$\mathrm{n_i}$	Lifetime of technology i (i∈A)	years
ι	Discount rate	-
ϵ_i	The CO_2 emissions emitted by technology i (i∈G)	kg/kWh
γ	CO_2 emissions from grey energy imported from the grid	kg/kWh
ϕ_i	Land use of technology i (i∈G)	km2/kW
ϕ_storage	Land use of energy storage	km^2/kWh
μ	Land use for biomass feedstock	km^2/kWh
υ_i	Visual impact of technology i	km^2/kW
	Variables	
Notation	*Description*	*Unit*
$\mathrm{E_i}(t)$	Energy generated by technology i at time t (i ∈G, t ∈T)	kWh
$\mathrm{E_{charging}}(t)$	Energy used to charge the energy storage (t ∈T) $\mathrm{E_{charging}}$ is positive if charging, negative if discharging	kWh
$\mathrm{E_{grid}}(t)$	Energy imported from the grid at time t (t ∈T) $\mathrm{E_{grid}}$ is positive if importing, negative if exporting energy	kWh
$\mathrm{IC_i}$	The installed capacity of technology i (i∈G)	kW
$\mathrm{IC_{storage}}$	The installed capacity of energy storage	kWh
$\mathrm{E_{deficit}}(t)$	The remaining deficit in energy supply at time t if only solar and wind are used (t ∈T)	kWh
$\mathrm{E_{stored}}(t)$	The energy that is stored in energy storage at time t (t ∈T)	kWh
$\mathrm{E_{import}}(t)$	Imported energy at time t (t ∈T)	kWh
LCOE	Levelized Cost Of Electricity	€/kWh
TAC	Total annual cost	€
TE	Total energy entering the system in a full year	kWh
$\mathrm{CapEx_i}$	Total investment costs incurred in installing technology i (i∈A)	€
EAC	Equivalent annual cost: CapEx annualized over the lifetime of the energy system	€
$\mathrm{YC_{total}}$	Total yearly recurring costs	€
$\mathrm{YC_i}$	Yearly recurring costs for technology i (i∈A)	€
$\mathrm{YI_{total}}$	Total recurring yearly income from selling electricity	€
TCI	Total yearly costs of importing energy	€
NPV	Net present value of all investments	€
$\mathrm{R_i}$	Yearly expected cashflow for technology i (i∈A)	€
IRR	Internal rate of return	-
SCO_2	Total system CO_2 emissions in one year	kg
RCO_2	Total emissions as a share of emissions if all energy was imported	-
LU	Total land use that is required to generate electricity	km^2
VIA	Total area that is visually impacted by wind turbines	km^2

4.3.2. Electricity generation from intermittent sources

The amount of energy generated by solar and wind ($\mathrm{E_i} \quad \forall i \in I$) at each time-step depends on the installed capacity of that generation method ($\mathrm{IC_i} \quad \forall i \in I$) and the capacity factor at time t ($\mathrm{CF_i}(t) \quad \forall i \in I$) and the size of the time-step τ.

$$\mathrm{E_i}(t) = \mathrm{CF_i}(t) \cdot \mathrm{IC_i} \cdot \tau \quad \forall i \in I \tag{4.1}$$

The capacity factor depends on the weather and is taken from the input data. This will be discussed in section 6.2. The size of the time-step equals 1 (hour). Electricity from solar and wind may not be enough to completely fulfill the energy demand ($\mathrm{ED}(t)$). There may be a deficit in available electricity ($\mathrm{E_{deficit}}(t)$), which is calculated by:

$$\mathrm{E_{deficit}}(t) = \mathrm{ED}(t) - \sum_{i \in I} \mathrm{E_i}(t) \tag{4.2}$$

4.3.3. Energy storage model

If there is a shortage in energy supply ($\mathrm{E_{deficit}}(t) > 0$) , the storage can fill in if there is enough energy available. If the solar panels and wind turbines produced more energy than is required ($\mathrm{E_{deficit}}(t) < 0$), energy can be stored by the energy storage. Charging and discharging, however, is not fully efficient. The conversion happens with a limited efficiency (η). When charging, less energy ends up being stored than it takes to charge. When discharging, more energy is discharged than it delivers. The charging and discharging efficiencies are assumed to have the same value in this research. The energy that is stored at time t ($\mathrm{E_{stored}}(t)$) is calculated by:

$$\mathrm{E_{stored}}(t) = \begin{cases} \mathrm{E_{stored}}(t-1) - \frac{1}{\eta} \cdot \mathrm{E_{deficit}}(t) & \text{if } (\mathrm{E_{deficit}}(t)) \geqslant 0 \quad \text{(discharging)} \\ \mathrm{E_{stored}}(t-1) - \eta \cdot \mathrm{E_{deficit}}(t) & \text{if } \mathrm{E_{deficit}}(t) < 0 \quad \text{(charging)} \end{cases} \tag{4.3}$$

The energy stored, however, needs to stay between zero and the installed storage capacity ($\mathrm{IC_{storage}}$). The amount of stored energy adheres to this inequality constraint:

$$0 \leqslant \mathrm{E_{stored}}(t) \leqslant \mathrm{IC_{storage}} \quad \forall t \in T \tag{4.4}$$

The energy from charging or discharging of the storage ($\mathrm{E_{charging}}(t)$) is positive if the energy storage is being charged and negative if being discharged. It can be calculated as:

$$\mathrm{E_{charging}}(t) = \mathrm{E_{stored}}(t) - \mathrm{E_{stored}}(t-1) \tag{4.5}$$

Equations 4.3 and 4.5 use the energy stored at time $t-1$ to calculate the energy stored at time t. If $t = 1$, however, this will not work. Therefore, the model is initialized with the energy storage filled for 50% :

$$\mathrm{E_{stored}}(0) = 0.5 \cdot \mathrm{IC_{storage}} \tag{4.6}$$

4.3.4. Energy from biomass

The energy generated by biomass is used to fill remaining deficits in supply as much as possible. It is only deployed if there is still a deficit in supply after energy storage is emptied and the costs of importing energy one kWh of energy at time t ($\mathrm{EP}(t)$) are higher than the variable costs of generating one kWh of energy from biomass ($\mathrm{VC_{biomass}}$).

$$\mathrm{E_{biomass}}(t) = \begin{cases} \mathrm{E_{deficit}}(t) - \mathrm{E_{charging}}(t) & \text{if } \mathrm{E_{deficit}}(t) - \mathrm{E_{charging}}(t) > 0 \text{ and } \mathrm{EP}(t) > \mathrm{VC_{biomass}} \\ 0, & \text{otherwise} \end{cases} \tag{4.7}$$

The amount of energy generated by the biomass ($\mathrm{E_{biomass}}(t)$) cannot be negative or exceed its capacity ($\mathrm{IC_{biomass}}$). Therefore, the energy generation from biomass adheres to the following inequality constraint:

$$0 \leqslant \mathrm{E_{biomass}}(t) \leqslant \mathrm{IC_{biomass}} \cdot \tau \quad \forall t \in T \tag{4.8}$$

4.3.5. Energy imports and exports modeling

In any energy system, supply must always equal demand. A connection to the main grid is used to ensure that supply and demand match exactly. Energy can be imported from the main grid when there is a shortage, or exported to the grid when there is a surplus. The energy imported from the national grid ($\mathrm{E_{grid}}(t)$) is calculated by:

$$\mathrm{E_{grid}}(t) = \mathrm{ED}(t) - \sum_{i \in I} \mathrm{E_i}(t) - \mathrm{E_{biomass}}(t) + \mathrm{E_{charging}}(t) \tag{4.9}$$

From this, it is clear that $\mathrm{E_{grid}}(t)$ has a negative value if energy is exported at time t and a positive value if energy is imported at time t. An extra variable is defined for energy imports from the grid ($\mathrm{E_{import}}$).

$$\mathrm{E_{import}}(t) = \begin{cases} \mathrm{E_{grid}}(t) & \text{if } \mathrm{E_{grid}}(t) > 0 \\ 0 & \text{Otherwise} \end{cases} \tag{4.10}$$

4.4. Mathematical formulation of the model outputs

The relevant model outputs to take into account have been defined in chapter 2.3. Below are the formulas used to calculate each of the relevant criteria.

4.4.1. Costs of the energy system

The first cost measure defined in chapter 2.3 is LCOE. The LCOE represents the average cost of generating one kWh in the entire system in "€/kWh". It is calculated by dividing the total annual system cost (TAC) by the total energy that has entered the system (TE) in one year:

$$\mathrm{LCOE} = \frac{\mathrm{TAC}}{\mathrm{TE}} = \frac{\mathrm{TAC}}{\sum_{t \in T}(\mathrm{E_{import}}(t) + \sum_{i \in G} \mathrm{E_i}(t))} \tag{4.11}$$

To be able to calculate LCOE, firstly, the total annual costs of importing and generating electricity must be calculated. Total costs for the system can be split up into three parts: a one-time investment (CapEx), a yearly recurring cost for operation and maintenance and the cost of importing energy. Total CapEx is calculated by summing the product of the investment cost per installed kW (κ_i) per technology with the installed capacity for each technology ($\mathrm{IC_i}$) :

$$\mathrm{CapEx_i} = \kappa_\mathrm{i} \cdot \mathrm{IC_i} \quad \forall i \in A \tag{4.12}$$

These investment costs are incurred only once. To be able to calculate the LCOE for the energy generation, the investment costs need to be annualized to Equivalent Annual Cost (EAC) over the lifetime of the investment. The EAC represents the equivalent annual payment that has the same value as the one-time capital expenditure at the beginning of the lifetime after discounting for the discount rate. Where ι represents the discount rate and n_i represents the lifetime of technology i.

$$\mathrm{EAC_{total}} = \sum_{i \in A} \frac{\mathrm{CapEx_i} \cdot \iota}{1 - (1 + \iota)^{-n_\mathrm{i}}} \tag{4.13}$$

The yearly recurring cost (YC) consists of two parts. Firstly, there is a fixed cost component (FC) in €/kW, recurring yearly regardless of the amount of energy generated. Secondly, there is a variable cost component (VC) in €/kWh, which depends directly on the amount of energy generated. The total YC is calculated by taking the sum of the YC of the generation technologies and the storage technologies.

$$\mathrm{YC_{total}} = \sum_{i \in G} \mathrm{YC_i} + \mathrm{YC_{storage}} = \sum_{i \in G} (\mathrm{FC_i} \cdot \mathrm{IC_i} + \mathrm{VC_i} \cdot \sum_{t \in T} \mathrm{E_i}(t)) + (\mathrm{FC_{storage}} \cdot \mathrm{IC_{storage}} + \mathrm{VC_{storage}} \cdot \sum_{t \in T} |\mathrm{E_{charging}}(t)|) \tag{4.14}$$

Energy enters the system in two ways: it can be generated in the system or imported. Up to now, only the cost of generation has been considered. Importing energy, however, also comes at a cost. The Energy Price at hour t (EP(t)) is taken from the data and will be discussed in section 6.2. The Total Cost of Importing energy (TCI) can be calculated by:

$$\mathrm{TCI} = \sum_{t \in t} (\mathrm{EP}(t) \cdot \mathrm{E}_{\mathrm{import}}(t)) \tag{4.15}$$

Now the Total Annual Cost that is required in equation 4.11 can be calculated by:

$$\mathrm{TAC} = \mathrm{EAC}_{\mathrm{total}} + \mathrm{YC}_{\mathrm{total}} + \mathrm{TCI} \tag{4.16}$$

4.4.2. Evaluating the attractiveness of the investment

In chapter 2.3, the importance of creating an energy system that is an attractive investment is stressed: the energy system needs to have an IRR that is higher than the Required Rate of Return. The IRR is defined as the discount rate (ι) at which the NPV equals zero. The NPV is a measure for the total value of the discounted cash flow that is associated with the investment. Discounting the cash flows takes into account the time value of money under a discount rate (ι). The investment is made in 'year zero', after which the project starts to earn itself back through an expected yearly cashflow for each technology (R). The discounted earnings for each year are summed over the lifetime of each technology.

$$\mathrm{NPV} = \sum_{i \in A} -\mathrm{CapEx}_{\mathrm{i}} + \sum_{i \in A} \sum_{y=1}^{n_{\mathrm{i}}} \frac{\mathrm{R}_{\mathrm{i}}}{(1+\iota)^{-y}} \tag{4.17}$$

Calculating the cashflows for the generation methods in G is relatively straightforward. The expected annual cashflow (R) after the initial investment is constant in every year and is calculated by subtracting the Yearly Cost (YC) from the Yearly Income (YI).

$$R_{\mathrm{total}} = \mathrm{YI}_{\mathrm{total}} - \mathrm{YC}_{\mathrm{total}} \tag{4.18}$$

The total yearly cost has been calculated in equation 4.14. The total Yearly Income is calculated by:

$$\mathrm{YI}_{\mathrm{total}} = \sum_{t \in t} (\mathrm{EP}(t) \cdot (\sum_{i \in G} \mathrm{E}_{\mathrm{i}}(t) + \mathrm{E}_{\mathrm{charging}}(t))) \tag{4.19}$$

The IRR can subsequently be found by solving 4.20 for the IRR:

$$\mathrm{NPV} = 0 = \sum_{i \in A} -\mathrm{CapEx}_{\mathrm{i}} + \sum_{i \in A} \sum_{y=1}^{n} \frac{\mathrm{R}_{\mathrm{i}}(y)}{(1+\mathrm{IRR})^{-y}} \tag{4.20}$$

4.4.3. Greenhouse gas emissions

One of the main goals of the regional energy transition is to reduce CO_2 emissions. Calculating the total emissions by energy generation in the system is done by multiplying the energy generation per method by the emissions caused per kWh generated ($\epsilon_{\mathrm{i}} \quad \forall i \in G$). Importing energy, however, also represents some emissions because the imported energy is generated with conventional energy sources. Emissions caused by imports is the product of energy imported from the grid and emissions per kWh of *grey* energy generated (γ). The total yearly system CO_2 emissions (SCO_2) are calculated by:

$$\mathrm{SCO}_2 = \sum_{t \in T} (\sum_{i \in G} (\mathrm{E}_{\mathrm{i}}(t) \cdot \epsilon_{\mathrm{i}}) + \mathrm{E}_{\mathrm{import}}(t) \cdot \gamma) \tag{4.21}$$

The variable that is of interest is the system CO_2 emissions compared to what the emissions would have been if all energy is imported: how many emissions are avoided? The Relative CO_2 emissions (RCO_2) are calculated by:

$$\mathrm{RCO}_2 = \frac{\mathrm{SCO}_2}{\sum_{t \in T} \mathrm{ED}(t) \cdot \gamma} \tag{4.22}$$

4.4.4. Evaluating land use and visual impact

Finding an objective way to measure land used by energy generation (LU) is not easy. In this research, a simplifying assumption is made that each wind turbine has a specific footprint, which is explained in the next section. For utility-scale solar, the same approach is applied. For residential solar, this footprint is zero, since it is placed on roofs and does not take any land. The footprints are denoted by $\phi_{\mathrm{i}}(\forall i \in A)$. A biomass plant also takes up some land. This is not the only effect of biomass on land use, however. Growing biomass feedstock also takes up land, depending on the amount of energy generated (μ).

$$\mathrm{LU} = \sum_{i \in A} (\phi_{\mathrm{i}} \cdot \mathrm{IC}_{\mathrm{i}}) + \mu \cdot \sum_{t \in T} \mathrm{E}_{\mathrm{biomass}}(t) \tag{4.23}$$

The Visual Impacted Area (VIA) caused by the energy system is calculated in a similar way. An assumption is made that wind turbines have a specific visual impact (υ_{i}), measured in ($\mathrm{km}^2/\mathrm{kW}$). Solar panels and biomass generation are not assumed to have any effect on visual impact. Therefore, these have a υ_{i} equal to zero.

$$\mathrm{VIA} = \sum_{i \in G} (\upsilon_{\mathrm{i}} \cdot \mathrm{IC}_{\mathrm{i}}) \tag{4.24}$$

This concludes the formulation of the simulation model. All calculations and outputs of the model have been defined. This simulation model will be used in an optimization. The optimization, including the objectives, constraints, and decision variables, will be introduced in the next chapter.

5

Description of the optimization problem and optimization method

Now that the simulation model and its outputs have been defined, this chapter defines the optimization problem that is solved to answer the main research question. After the optimization problem has been completely defined, the method used to solve the optimization is explained. The choice for performing a multi-objective optimization is motivated first.

5.1. Choice between single- or multi-objective optimization

In chapter 2.3, four important criteria are defined. The criteria are all found to be important for deciding on the optimal generation mix, and some criteria, such as minimizing land use and minimizing capital expenditure, may be conflicting. Therefore, it is desirable to include multiple objectives in the optimization instead of focusing on cost minimization as many other studies do. There are two main ways of including multiple objectives: aggregating all objectives to a single function (scalarization) or performing a multi-objective optimization. In this research, a multi-objective optimization is performed. That means that the goal is to find the Pareto-front for this multi-objective optimization problem. This approach has several advantages.

The outcome of a multi-objective optimization is a Pareto-front: many solutions are obtained, all performing better on some aspects. Comparing all these outcomes will result in more insight into the functioning of the system and allow decision-makers to take into account the different trade-offs involved. Socio-technical problems seldom have one single optimal solution and aggregating the results to one solution oversimplifies the choice of generation mix. The optimal solution depends on the preferences of the stakeholders involved. Several interesting solutions from a Pareto-front can be taken and used as a basis for discussion. This is not possible when the objectives are scalarized. Although multi-objective optimization knows many benefits, some limitations of multi-objective optimizations also need to be discussed.

5.1.1. Limitations of multi-objective optimizations

Two main limitations of multi-objective optimization need to be taken into account. The first limitation is that analyzing the results of a multi-objective optimization can prove to be quite difficult. There is not one single result. When only two objectives are involved, one can still plot the results. When analyzing more than two objectives, analyzing the results becomes a real challenge. In chapter 7, the approach taken in this research is explained.

The second limitation is that the amount of objectives one can include is limited by computing power. For M conflicting objectives, there exists a hypersurface with M-1 dimensions. To get an accurate representation of this hypersurface, the amount of necessary points found on the hypersurface increases exponentially with M (Coello et al., 2005, p.21). This means that a high sample size is necessary if many objectives are included. If a sample of 60 solutions were enough to represent two objectives, for four objectives, the required sample size would be almost 220 thousand. When the amount of objectives increases, the amount of locally non-dominated solutions increases exponentially. This is also intuitively true: with more conflicting objectives, it is soon impossible to improve on a specific objective without negatively affecting at least one other objective.

A maximum of three objectives will be included in this research to keep the required sample size manageable. With three objectives, taking around 3600 samples is enough to represent the Pareto frontier, assuming that 60 samples are sufficient for two objectives. The choice for a multi-objective optimization has been motivated and some limitations of multi-objective optimizations have been discussed. The next section will specify the optimization problem.

5.2. Defining the optimization problem

In order to have completely defined the optimization problem, three things need to be specified: the decision variables, the constraints, and the objectives of the optimization. These three parts will now be discussed.

5.2.1. Defining the decision variables

Decision variables are the variables which are controlled by the decision-maker in order to influence the outcome. In this research, the decision variables are the installed capacities of the considered technologies. The goal is to find a set of optimal combinations of installed capacities given the constraints (in kW for generation, kWh for storage). The decision variables (DV) are defined by:

$$DV_1 = IC_{\text{wind V66}} \tag{5.1}$$

$$DV_2 = IC_{\text{wind V110}} \tag{5.2}$$

$$DV_3 = IC_{\text{residential solar}} \tag{5.3}$$

$$DV_4 = IC_{\text{utility-scale solar}} \tag{5.4}$$

$$DV_5 = IC_{\text{biomass}} \tag{5.5}$$

$$DV_6 = IC_{\text{storage}} \tag{5.6}$$

5.2.2. Defining the constraints

The optimization model in this research is a constrained optimization model. The solution space is constrained by several constraints that the solution needs to satisfy. These constraints will now be discussed. The choice of constraints is an important consideration. Therefore, for each of the constraints that have been defined, the reasoning behind the constraint is given.

The optimal generation mix will be determined for different levels of reduction in CO_2 emissions. CO_2 reduction is therefore included as a constraint. The total CO_2 emissions in the region as a percentage of emissions without RES-E in the region (defined in equation 4.22) must be smaller than a specific number (β):

$$RCO_2 < \beta \tag{5.7}$$

Three different scenarios will be evaluated with different values for β. Which will be discussed in section 6.5.

The second constraint is a constraint on land use. The energy system cannot use more land than is available in the region. The assumption is made that only land that is currently used for agriculture (excluding greenhouses) can be used for energy generation. The total land use (LU) must be smaller than the available (agricultural) land (AL) in the region.

$$LU < AL \tag{5.8}$$

Land use has been defined in equation 4.23. In section 6.1, the region that is evaluated in this research is introduced and the available agricultural land is defined.

The third constraint is a constraint on IRR. For investments in the energy system to be feasible, the system must have at least the Required Rate of Return (RRR), as was explained in section 2.3.2. If this RRR is not reached, there will not be any interested investors, since they are just as well of investing their money in a completely risk-free project. Only the solutions that result in an IRR that is bigger than the Required Rate of Return are considered to be feasible alternatives.

$$RRR < IRR \tag{5.9}$$

The equation for IRR has been given in equation 4.20. The RRR is usually equal to a company's Weighted Average Cost of Capital (WACC). The WACC represents the return a company must receive on an investment for the investment to be profitable. It is beyond the scope of the research to go into this any further. For this research, an RRR of 3% is assumed. This is a typical value for the cost of debt (KPMG, 2017a).

The fourth constraint is a constraint on the total electricity that is generated annually within the region. By minimizing LCOE (combined with the assumption that all energy can be sold to the grid at all times), some solutions on the Pareto-front will have unrealistically high installed capacities. The reason for this is that importing energy is expensive: a lower LCOE is achieved if more energy is generated within the region. To have a set of realistic results, the total annually generated electricity has been constrained to a maximum in this research. The maximum production compared to the total energy demand in the region is set at 3 in this research.

$$\sum_{t\in T}\sum_{i\in G} E_{\mathrm{i}}(t) < 3 * \sum_{t\in T} ED(t) \tag{5.10}$$

The fifth constraint has to do with land use by biomass. Biomass production is most realistic on land that is already suited for crop production, not on land that is used for grazing (Johansson & Azar, 2007). It is therefore assumed that biomass can only be produced on cropland. Convincing all farmers to produce biomass is not realistic and may lead to high food prices (Ignaciuk et al., 2006; Johansson & Azar, 2007). Therefore, the percentage of available cropland (CL) that can be used for biomass production is limited to 33%. Transforming 33% percent of cropland is already a stretch, but it is more realistic than transforming 100% of cropland.

$$\mu * \sum_{t\in T} E_{\mathrm{biomass}}(t) < 0.33 * CL \tag{5.11}$$

The final constraint that is applied has to do with the available roof surface. Residential solar consists of solar panels placed on rooftops. The total surface area used by the residential solar panels has to be less than the Suitable Roof Surface (SRS). The available roof surface per region was studied by Broersen (2018) and will be discussed in section 6.1.

$$\phi_{\text{Utility-scale solar}} * \mathrm{IC}_{\text{Residential solar}} < SRS \tag{5.12}$$

In this section, constraints have been defined by using a 'less-than' condition. This is not common practice in optimizations. Typically, 'less-than-or-equal-to' conditions are used because at the edges of the solution space is where interesting results can be found. For this research, using a 'less-than' condition does not alter the results, although further research should use 'less-than-or-equal-to' conditions. This is further discussed in appendix C. The objectives used in the optimization are defined next.

5.2.3. Defining the objectives

Chapter 2.3 defined four important criteria for choosing the generation mix of a regional energy system. As was discussed in section 5.1, the criteria will not be aggregated to one objective function. Section 5.1.1, showed that a maximum of three criteria can be included as an objective. Including all four important criteria (LCOE, CapEx, Land Use and Visually Impacted Area) in the optimization is therefore not possible. A choice needs to be made about which criteria are most important to include as objectives in the optimization. It is important to mention that the criterion that is not included as an objective will still be taken into account when comparing the different solutions, which will be further discussed in chapter 7.

From chapter 2.3, it is clear that most actors consider LCOE to be an essential consideration. Therefore it will be included as an objective.

There are three criteria left to consider: land use, Visually Impacted Area (VIA), and capital expenditure. A choice is made to include land use. In a country as densely populated as The Netherlands, minimizing land use is a critical issue, as was already explained in section 1.2.2 and 2.3.4. Solutions that use more land will mean that the process of allocating land and changing destination plans will take up more time, and the goals set in the climate accord may not be reached.

Finally, the Visually Impacted Area is included as an objective. There are two reasons for including the Visually Impacted Area instead of the CapEx. The first reason is that minimizing the Visually Impacted Area is considered to be important by many actors. Minimizing CapEx is only relevant to investors. The second reason is that including VIA has a bigger impact on the final result. Including CapEx does not change the results as much. Although not ideal, it is concluded that the optimization results in a representative Pareto-front, even when CapEx is excluded as an objective. The comparison is provided in more detail in appendix D.

Equations for the objectives have been given in section 4.4. To summarize this section, the objectives to be minimized in the optimization are:

1. *Levelized Cost of Electricity*
2. *Land Use*
3. *Visually Impacted Area*

Now that the optimization problem has been defined by specifying the decision variables, the constraints, and the objectives, the next section will describe the method that is used to solve the optimization problem.

5.3. Description of the optimization algorithm: NSGA-II

The optimization problem has now been fully defined. In this section, the algorithm used to solve this problem is introduced.

5.3.1. Choosing an optimization method for this research

In this research, a genetic algorithm called the Non-dominated Sorting Genetic Algorithm II (NSGA-II) is used to find the set of Pareto optimal solution. A genetic algorithm is an artificial intelligence technique that is widely used to solve multi-objective optimization problems. It offers a high degree of flexibility and can handle non-linear functions. Genetic algorithms are specifically suited for finding the Pareto-front in a multi-objective optimization because they evaluate multiple solutions in a single iteration, finding multiple points on the Pareto-front in one run. Also, genetic algorithms can deal with concave and discontinuous Pareto-fronts in contrast to many mathematical methods (Chang, 2015). Because of these qualities, a genetic algorithm is the optimization algorithm of choice in this research. Several genetic algorithms have been developed specifically for multi-objective optimizations (Konak et al., 2006).

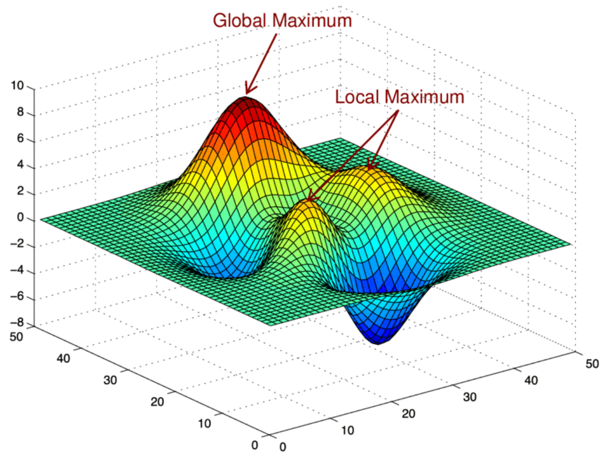

Figure 5.1: Visualization of local and global optima for a single-objective optimization problem with two decision variables. Reprinted from Jin (2015)

Of all the genetic algorithms that have been developed for multi-objective optimization, NSGA-II developed by Deb et al. (2002) is one of the most widely used (Golchha & Qureshi, 2015). It is also used in this research. NSGA-II is well tested and efficient (Konak et al., 2006). The NSGA-II algorithm is flexible: there is no direct limit on the number of objectives or constraints that can be included. Also, it has an advanced mechanism to ensure a diverse set of solutions throughout the decision space. This ensures that the optimization does not get stuck in a local optimum while searching for globally optimal solutions and a complete representation of the Pareto-front is found. A representation of global and local optima for a two-objective problem is provided in figure 5.1. Although the NSGA-II algorithm is well-suited for multi-objective optimization and widely used, the performance was not compared to other algorithms. The performance is more than sufficient for this research, but it is conceivable that another algorithm finds an even closer approximation of the Pareto-front. The next paragraph describes a simplified explanation of the workings of NSGA-II.

5.3.2. Simplified explanation of the NSGA-II algorithm

The NSGA-II algorithm works based on an evolutionary process. It starts with an initial population that is made up of a random set of individuals. Each individual is a vector of the decision variables. In this case, each individual is a vector of installed capacities per electricity generation method. The fitness of the individuals with regards to the different objectives is determined, and the population is ranked based on domination and the proximity to other solutions (the so-called *crowding distance*). Solutions that dominate other solutions and are not as close to other solutions are ranked higher and have a higher chance of propagating into the next generation. Subsequent generations are generated by combining different individuals and by random changes to a single individual. The algorithm keeps creating new generations until a certain stopping criterion is reached. The final population is the output of the algorithm. A simplified flowchart of the NSGA-II algorithm is presented in figure 5.2.

In this report, the exact mathematical formulation of the optimization algorithm is not discussed as it is not of further relevance to the analysis of the results. If the reader is interested in the mathematics behind the NSGA-II algorithm, a more detailed flowchart and mathematical formulation are given by Golchha & Qureshi (2015). The next section will explain the choice of modeling tool employed in this research before the input parameters for the NSGA-II algorithm are defined.

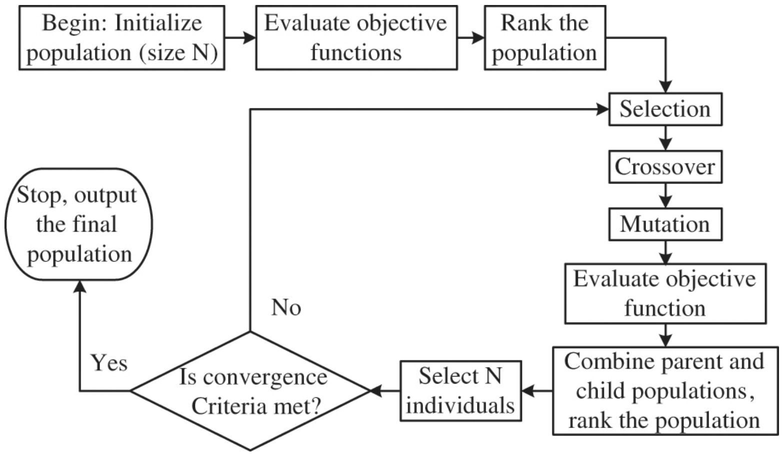

Figure 5.2: Flowchart of the NSGA-II genetic optimization algorithm. Reprinted from Reddy & Bijwe (2017)

5.4. Choice of modeling tool

Since a customized energy systems model needs to be developed and a multi-objective optimization is required, using an existing energy systems modeling tool was not an option. For this research, a new multi-objective optimization model needed to be constructed. Building a multi-objective optimization model can be done in different programming environments such as Python, C++, or Matlab. In this research, Python has been selected as the programming language of choice. There are two main reasons for this. Firstly, Python is highly flexible and many packages have been developed which add different functionalities to Python (including packages for multi-objective optimization). Secondly, Python is a widely-used programming language: using Python will enable other researchers to use the model.

5.4.1. Choice of multi-objective optimization package in Python

To perform the multi-objective optimization, a package called *Platypus* (Hadka, 2019) in Python is used. The main criteria in selecting the optimization package to be used were that it includes optimization through NSGA-II and that it is straightforward to implement. Performance was not as important, although Platypus was found to perform excellently.

Platypus is easy to implement. It allows for easy customization of the objectives, constraints, and decision variables. It includes most of the well-known multi-objective optimization algorithms such as NSGA-II, MOPSO, and EpsMEOA. With Platypus, it is possible to change some key parameters, but full customization of the algorithm is not included. For this research, this was not an issue. Other researchers may also consider the following packages for more customizability: DEAP, Inspyred or PyGMO.

The NSGA-II optimization algorithm in Platypus requires some input parameters such as a stopping criterion and a population size. These input parameters will now be discussed.

5.5. Defining input parameters for the optimization algorithm

Several inputs are required to run the multi-objective optimization with the NSGA-II algorithm through Platypus. The two most important inputs are population size and a stopping criterion.

The **population size** of a genetic algorithm represents the number of combinations of inputs that will be evaluated in each generation. The population size is also equal to the number of final solutions which the algorithm presents. A larger population results in a more complete representation of the Pareto-front but increases computing time. A population size of 3000 is chosen for this research. As discussed in section 5.1.1, this research uses three objectives. Using a population size of 3000 for three objectives corresponds to using a population size of around 55 for two objectives (as explained in section 5.1.1. Although no exact measure exists for this, it is considered to be sufficient to describe the complete Pareto front.

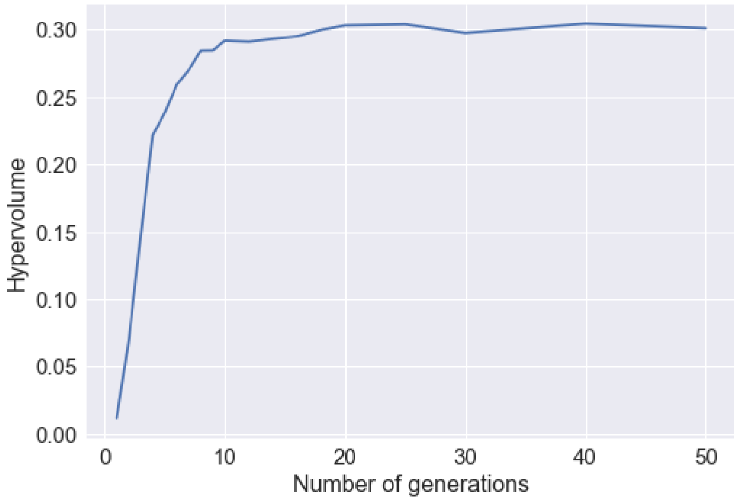

Figure 5.3: Hypervolume with increasing number of generations

Once the **stopping criterion** is reached, the algorithm stops the optimization. In this research, the algorithm is stopped once a certain number of generations has been evaluated. It is important to be sure that the algorithm has converged towards the 'true' Pareto front before stopping, but increasing the number of generations will directly increase run-time. To test for convergence, a commonly used measure is the 'hypervolume' spanned by the Pareto front (Emmerich et al., 2005). A larger hypervolume indicates that the objectives have been 'optimized more' than with a lower hypervolume. The goal is to optimize until the hypervolume no longer increases, indicating that the algorithm has converged on a set of optimal solutions.

Figure 5.3 shows the convergence of the optimization. The figure represents the average convergence of the algorithm after three runs. It is clear that after around ten generations, the algorithm has already converged towards an optimum. In this research, to be sure of convergence, 50 generations is set to be the stopping criterion. More research indicated that hypervolume does not significantly increase even after 200 generations.

Running the population of 3000 for 50 generations means that the simulation model needs to be evaluated 150.000 times. The model that is created runs very quickly, and each function evaluation only takes 27ms. Therefore, running 150.000 simulations takes around one and a half hours. This is a long time, but running multiple successive optimizations overnight meant that this was not a big barrier. The slowest element of the simulation model is the storage model because it requires inputs from the previous time step for each new time step. If storage is excluded, run-time is only 7ms per evaluation.

Several other parameters of the algorithm can also be adjusted, such as the way in which the first generation is formed, the mutation process, the cross-over process, and the process of the selection of individuals. After some experimentation, it was found that changing these parameters does not significantly improve the results. The results generated with the standard settings for these additional parameters for the NSGA-II algorithm in Platypus are already sufficiently spread out over the Pareto front. Therefore, standard settings for NSGA-II in Platypus are used.

Now that the optimization problem and the method used to solve the optimization problem have been identified, the next chapter will describe the region that is used as a case-study, the data input and will verify the behavior of the optimization model.

6

Definition of the case study, data input and model parameters

In the previous chapters, the background, goals of the model, and the mathematical formulation have been defined. This chapter will introduce the region that is used as a case-study in this research and the data used in the model. To conclude the chapter, section 6.4 verifies that the model behavior corresponds to the expected behavior of the conceptual model and section 6.5 defines the set-up of the experiments.

6.1. Choice for the region to be analyzed as a case-study and associated data

Up to now, this report has been written in a general way; all research up to this point is relevant for any region within The Netherlands. The model is also generic; it can use data input for any region. Although the model that is described is not specific to a Dutch electricity system, the actors involved may be different. To apply the model to other regions, the data for other regions can be collected from the same sources presented in this chapter.

In this research, the choice is made to apply the model to the region Goeree-Overflakkee (or Goeree in short) in The Netherlands, which is one of the 30 Dutch regions defined in the Regional Energy Strategy (Rijksoverheid, 2019). Goeree is a region in the province of Zuid-Holland that is assumed to be representative for a rural region in The Netherlands. The municipality in Goeree has set the ambition to be energy neutral before 2020 and plans are being made to be completely independent of energy imports. Some data is needed for the region of Goeree to be able to define the model completely. Table 6.1 provides a summary of this data.

Goeree has a population of almost 49.500 citizens. The land surface of Goeree is 262 km^2, resulting in a population density of 189 citizens/km^2. This is significantly less than the national average of around 411 citizens/km^2. In Goeree, around 130 km^2 is used for different types of agriculture (excluding greenhouses). It is assumed that, theoretically, all of this 130km^2 can be used to generate electricity. Of this 130 km^2, around 25 km^2 is used for grazing (CBS, 2019b). Grazing lands are not immediately suitable for biomass production. The cropland, suitable for biomass, is therefore 105 km^2.

A report by Deloitte investigating the roof surface suitable for solar power generation in The Netherlands found that around 3.4 km^2 of roof surface in Goeree is suitable for solar panels (Broersen, 2018). Assuming that not all these roofs are oriented towards the south and available, 75% of this value (2.55 km^2) is taken as the maximum area available for solar panels oriented southward in the region. The surface taken per kW of installed solar is defined in section 6.3.2. Taking this into account, the maximal installed capacity in residential solar is around 85MW in Goeree.

Table 6.1: Data on the evaluated region regarding population and surface area (sources in text).

	Population	**Surface area**			**Roof surface**	
		Total (km^2)	Agriculture (km^2)	Cropland (km^2)	Available (km^2)	Suitable (75%) (km^2)
Goeree	49.500	262	130	105	3.4	2.55

6.2. Data input used in the model

To be able to analyze the energy system, the model requires some data input. In this research, the following sets of data are used as input and will be discussed below:

1. Hourly demand data for the considered region
2. Hourly energy prices in The Netherlands
3. Hourly data on the capacity factor of solar panels in the region
4. Hourly data on the capacity factor for different types of wind turbines in the region

For each data-set, the source of the data will be discussed, including any concerns about reliability or quality of the data. Also, the data will be visually inspected in order to validate that the data is consistent with common sense and other research. The figures in this chapter are generated for the purpose of this research based on the data described.

6.2.1. Hourly energy demand

There is no data directly available for the demand in the region of Goeree. To approximate a representative data-set for demand in Goeree, the national electricity demand is adjusted for the population size of Goeree. This assumes that the demand profile of Goeree is consistent with the national demand profile. The national energy demand has been retrieved from the transparency platform of the European Network of Transmission System Operators for Electricity (ENTSO-E) (ENTSO-E, 2019). The ENTSO-E publishes the demand data per European nation every year. The data is published with a resolution of 15 minutes. To obtain hourly data, the data is aggregated to the average demand each hour. In this research, the ENTSO-E data from 2018 is used, since this is the latest available complete data-set. The energy generation data (see section 6.2.3) is taken for the year 2014. Unfortunately, no demand data is available for 2014. The analyses performed with the data are still expected to be valid because weather data and demand data are not very highly correlated.

The data quality of the demand data was quite good, most values were included and consistent regarding data type. There were only two missing values, which were filled by taking the value from the hour before.

Evaluation of the demand data

A daily, weekly, and seasonal pattern can be expected. To verify this, the left figure in figure 6.1 shows the daily average energy demand for a full year. The seasonal pattern is clear.

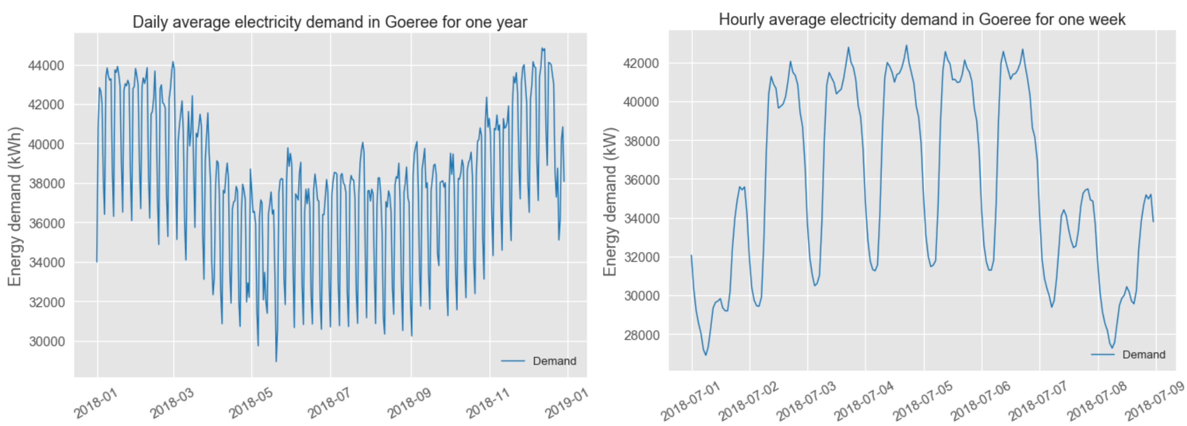

Figure 6.1: Evaluating the demand data for Goeree-Overflakkee: daily and hourly average demand. On the left is the average electricity demand in Goeree per day for one year, showing a clear seasonal pattern and weekly. On the right, the average electricity demand in Goeree per hour from Sunday to Saturday is shown. This shows a clear daily and weekly pattern.

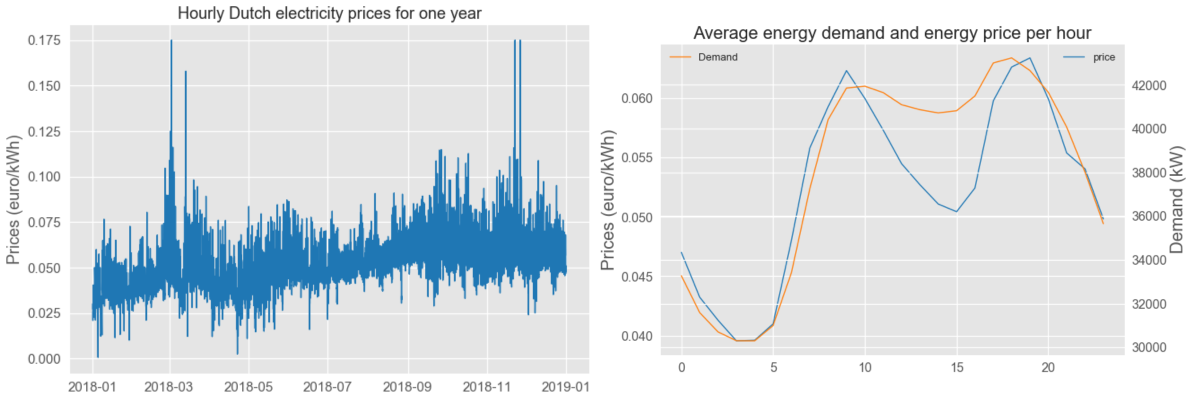

Figure 6.2: Evaluation of the data on Dutch energy prices. The figure on the left shows the hourly energy prices for one year. The figure on the right compares the average hourly energy price to the average hourly energy demand over a year.

Electricity demand is a bit lower in summer, compared to demand in the winter. The right figure in figure 6.1 shows the hourly energy demand for one week. From this figure, the daily pattern is clearly visible. The valleys are during the night, and the peaks are during the day. A weekly pattern can also be observed, with lower demand during the weekends and higher demand on weekdays. The patterns in the data are as expected.

6.2.2. Hourly energy prices

To be able to calculate the price of energy imports and to calculate the earnings from energy generation (for the NPV and IRR calculations), data on hourly energy prices is required. This data was obtained from the ENTSO-E. Data for 2018 is used. This is the latest data-set available and it is the same year as the demand data.

In this research, day-ahead prices were used. On the energy trading market, most energy is sold by producers to energy consumers on the day before the energy is produced (and consumed). This is the so-called day-ahead market. There is also a real-time market, which is meant to sort out any imbalance issues. The prices on the real-time market are more volatile, and the day-ahead market is more representative of the actual energy prices.

Evaluation of the data on day-ahead prices

From figure 6.2, it can be seen that the energy prices are quite volatile. There is also a strong correlation between energy demand and the energy price, as can be expected. Demand and prices are lowest at night and have peaks at the beginning and the end of the day. In general, the prices are between 25 and 80 €/MWh. The average energy price is 52 €/Mwh.

6.2.3. Hourly solar PV power output

The output of solar panels depends on the capacity factor (see equation 4.1). The capacity factor changes depending on temperature and solar irradiation. In this research, data collected by Pfenninger & Staffell (2016) is used. The data on the capacity factors for solar and wind can be retrieved from www.renewables.ninja (2019).

To calculate the output of the solar PV panels, Pfenninger & Staffell (2016) use the Global Solar Energy Estimator (GSEE) model. It takes into account the temperature of the panel, angle of the sun and the panel, estimated direct and diffuse irradiance onto the panel and a parameter for system loss. In this research, the angle of the solar panels is taken to be 35 degrees and all panels are assumed to be southward facing. Pfenninger & Staffell (2016) found a system efficiency of about 90% with a standard deviation of 4%. Therefore, a system loss of 10% has been included in the power output calculation. For the data about the temperature and irradiance, NASA's MERRA-2 database was used, which is a retrospective database of global weather data.

Evaluation of solar PV output data

The output from solar panels clearly shows a seasonal pattern as can be seen from the left figure in figure 6.3. The average daily capacity factor is significantly higher in summer than

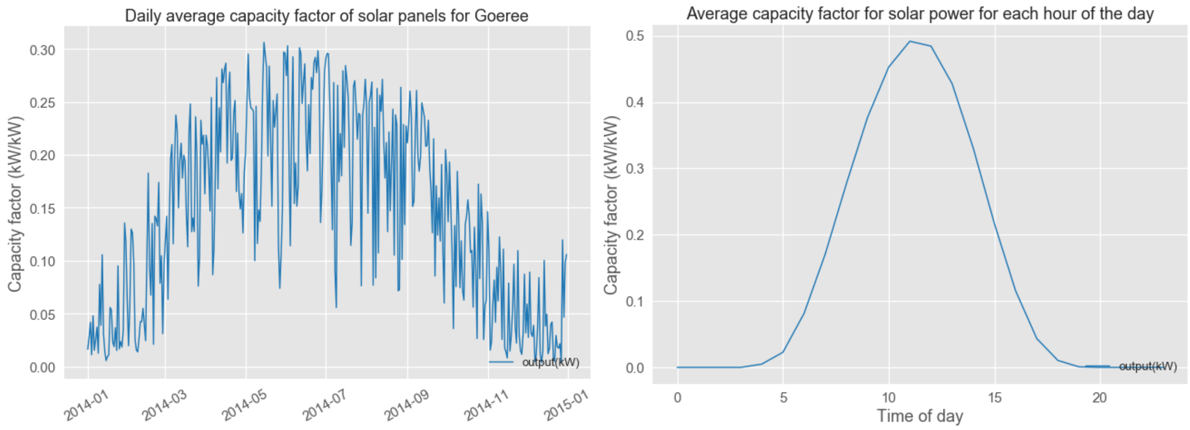

Figure 6.3: Evaluating the data on the capacity factor for solar panels. The left image shows the daily average capacity factor for solar panels throughout a full year. The image on the right shows the average capacity factor for each hour of the day.

in winter. This is to be expected. Also, the average hourly pattern shown on the right in figure 6.3 corresponds with the expected pattern. Most energy is generated around the middle of the day, with no energy being generated at night. The average capacity factor for solar panels is 14.6%. This value is a bit lower than the global average of 17.6% (IRENA, 2017b). This is to be expected since The Netherlands does not have the warmest of climates. From the figure, it is clear that solar power is a very intermittent source of power, fluctuating significantly from hour-to-hour and day-to-day.

6.2.4. Hourly wind power output

For wind turbines, the capacity factor depends on several variables, including wind speed and air density. In this research, data collected by Staffell & Pfenninger (2016) is used. It is only available for the year 2014. To calculate the output of the wind turbines at different wind speeds, Staffell & Pfenninger (2016) use the Virtual Wind Farm (VWF) model. The weather data concerning wind speeds, air density, and temperature were taken from NASA's MERRA-2 database. The MERRA-2 database approaches each grid cell as a flat surface, and the orology is not taken into account. The Netherlands is very flat, so this is not an issue.

In this research, two wind turbines are used: a Vestas V66 turbine with a rated power of 1750kW and a rotor diameter of 66 meters, and a Vestas V110 turbine with a rated power of 2MW and rotor diameter of 110 meters. These turbines have separate input data for the capacity factors. The data is retrieved from www.renewables.ninja (2019). The exact turbine types that were used in this research are also in the database. The weather data from NASA's database is combined with the specific power curves that are provided by the producers of the turbines (Vestas).

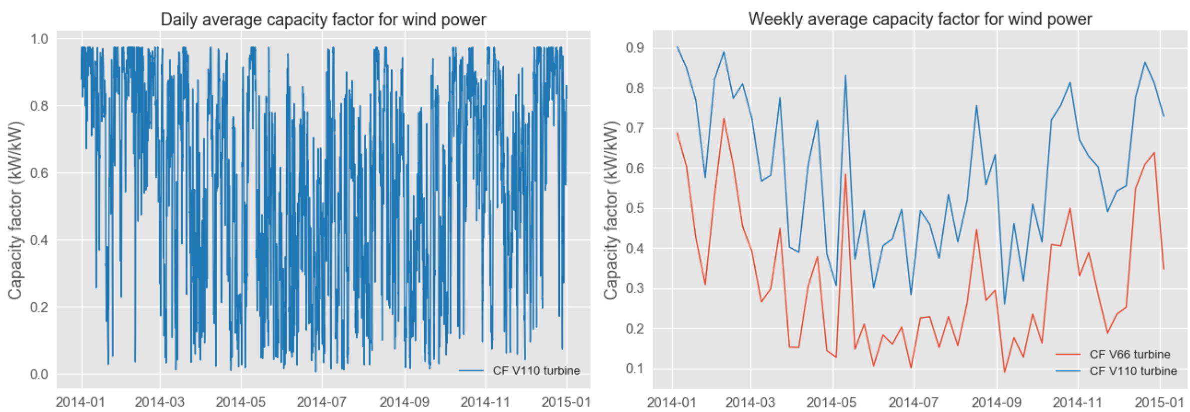

Figure 6.4: Evaluating the data on the capacity factor for wind turbines. The image on the left shows the daily average capacity factor for a big (V110) wind turbine. The figure on the right compares the weekly average capacity factors for smaller (V66) wind turbines and bigger (V110) turbines

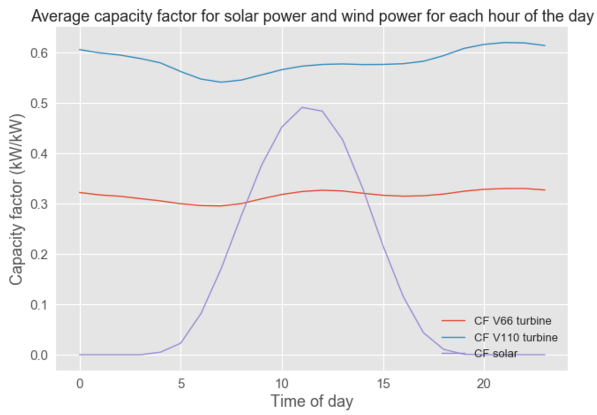

Figure 6.5: Comparing the average hourly capacity factor for wind turbines and solar panels: for wind turbines, the correlation between time of day and capacity factor is not as significant as for solar panels.

Evaluation of wind output data

From figure 6.4, it can be seen that the capacity factors for wind turbines vary significantly day-to-day. From the image on the right, it is clear that there is a seasonal pattern in the data for the capacity factor of wind turbines: more energy is produced in the winter months than in the summer months. The energy supply can clearly be seen to be very intermittent. Production varies greatly. From day to day, the average can even vary from no generation at all to production at full capacity.

From the same figure, it can be seen that smaller wind turbines have a smaller capacity factor compared to bigger turbines. This effect is mainly due to larger wind turbines having a bigger hub-height. At higher altitudes, the wind speed will be higher as well.

Figure 6.5 shows that the average capacity factor for wind turbines is not significantly dependent on the hour of the day, in contrast to the capacity factor for solar panels.

6.3. Defining economic and technological parameters

As is clear from the conceptualization of the model, the data input for demand, generation, and prices is not the only information that is required. Several technological parameters need to be defined as well. The most important parameters are several metrics for costs, emissions per generated kWh for each technology, and the land use for each technology. Section 6.3.1 will discuss costs and emissions, followed by the land use per technology in section 6.3.2.

6.3.1. Techno-economic parameters of the energy system

Table 6.2 shows the used parameters for the energy generation technologies regarding cost and CO_2 emissions. Several cost parameters are given. The investment cost per installed kW (CapEx) is given for each technology. The operational costs are split up into Fixed Operation and Management costs (FOM), which are independent of energy production, and the Variable Operation and Management costs (VOM), which depend on the amount of energy generated. Many sources exist to find these parameters and significant differences between given values exist. The values that are shown in table 6.2 were found to be representative for each technology. The data is taken from reports from well-regarded institutes, which used large data-sets. De Pater (2016) compared five different sources and the values that were found are comparable with the values used in this research. Therefore, we conclude that the values used in this research are representative. For energy from the grid, a value for average CO_2 emissions for *grey* energy in The Netherlands is taken. The VOM for biomass also includes the fuel cost that is associated with the biomass feedstock. For storage, a conversion efficiency (η) of 90% is assumed. This is consistent with what is found in literature by De Pater (2016).

6.3.2. Land-use for electricity generation

The values that have been used for land use per technology are shown in table 6.3. For residential solar, no additional land is required since they are placed on roofs. For utility-

Table 6.2: Costs and emissions of energy generation methods and energy storage. The units for CapEx are *€/kW* for energy generation and *€/kWh* for energy storage. Units of FOM are *€/kW/y* for the generation technologies and *€/kWh/y* for storage.

		CapEx	FOM	VOM (€/kWh/y)	Lifetime (y)	CO_2 emissions (kg/kWh)	Source
Solar							
	Residential	1250	17	0	25	0	*KIC InnoEnergy (2015)*
	Utility-scale	850	27	0	25	0	*KIC InnoEnergy (2015)*
Wind							
	Wind turbine	1600	40	0	25	0	*IRENA (2017b)*
Biomass							
	Biomass	2300	70	0.019	25	0.075	*IRENA (2012)*
Grid energy							
	Grey energy	-	-	-	-	0.355	*CE Delft (2015)*
Energy storage							
	Short-term storage	400	10	-	5	-	*IRENA (2017a)*

scale solar, there is a land requirement. From literature, it is found that this value is around 30 $\mathrm{m^2/kW}$. This results in an energy density of around 33 $\mathrm{W/m^2}$.

For wind turbines, the value is based on own calculations, which are tested through literature. In literature, no distinction is made between big and smaller wind turbines, although this is necessary for this research. Wind farms take a large amount of space because wind turbines need to be separated by a certain distance. Currently, most wind farms use around 7.5 rotor diameters between turbines, but research suggests that an optimal spacing may be up to 15 rotor diameters apart (Meyers & Meneveau, 2012). Because the spacing distance is determined by rotor diameter, bigger turbines require more space. To calculate the land used by one wind turbine, it is assumed that turbines are spaced 7.5 rotor diameters (D) apart. This is represented in figure 6.6. The area that one wind turbine takes can be calculated by taking $(7.5 * D)^2$. After dividing by the rated power of the turbines, this results in a value of 140 $\mathrm{m^2/kW}$ for the smaller (V66) turbine and 340 $\mathrm{m^2/kW}$ for the large (V110) turbine. These values were tested in literature and are within the range specified by Denholm et al. (2009) and also within the range specified by Palmer-wilson et al. (2019). Therefore, it is concluded that these values accurately represent the land used by wind turbines.

For electricity from biomass generation, land use consists of two parts. The biomass plant uses some land. This is the 'fixed' part of the land use. To produce biomass feedstock, a significant amount of land is required. Fthenakis & Chul (2009) evaluated the land needed to produce a yearly feedstock for the biomass plant. An assumption is made that no land is required for energy storage. The land necessary to store relatively large amounts of energy in batteries will likely be small and no specific data could be found on this.

6.3.3. Visual Impact of wind turbines

From chapter 2.3, it was clear that minimizing the visual impact of the energy system is important. The visual impact is mainly caused by wind turbines, which stand high and are a nuisance to some. In this research, an attempt is made to quantify the visual impacted

Table 6.3: Land use per technology. The land use has been split up into a fixed component which depends on the installed capacity (independent of generation) and a variable component, which depends on the amount of energy generated. Sources which are not presented in the table, are discussed in the text.

		Fixed land use ($\mathrm{m^2/kW}$)	Variable land use ($\mathrm{m^2/kWh}$)	Source
Solar				
	Residential	0	0	Palmer-wilson et al. (2019); Denholm & Margolis (2008) Ong et al. (2013)
	Utility-scale	30	0	
Wind				
	Vestas V66	140	0	-
	Vestas V110	340	0	-
Biomass				
	Biomass plant	5	0.4	Fthenakis & Chul (2009)
Energy storage				
	Short-term storage	0	0	-

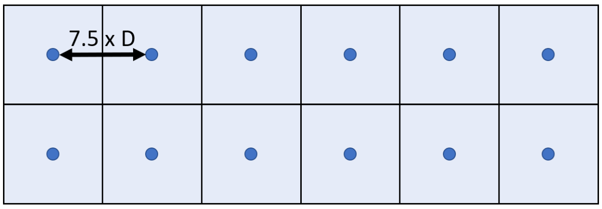

Figure 6.6: Visualization of land use by wind turbines. Wind turbines in a windfarm have a spacing of 7.5 rotor diameters. Each dot represents one wind turbine.

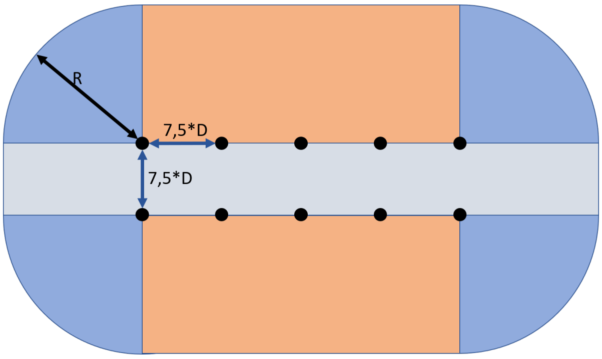

Figure 6.7: Visualization of the visually impacted area of wind turbines.

area by wind turbines. This is done by looking at studies that analyze the distance from which a wind turbine is observed. Before analyzing the visual impact of one wind turbine, an assumption is made that wind turbines are placed in wind farms of 5 by 2 wind turbines. Figure 6.7 shows the area that is visually impacted (VIA) by a wind farm. The total area is found by summing the blue area$^{(1)}$, grey area$^{(2)}$ and orange area$^{(3)}$. The impact of one turbine is calculated by dividing this total area by the number of wind turbines. It is calculated by:

$$VIA = \frac{^{(1)}(\pi * R^2) +^{(2)} ((w * 7.5D + R) * h * 7.5D) +^{(3)} (R * w * 7.5D)}{w * h} \tag{6.1}$$

Where D is the rotor diameter, w is the number of turbines over the width of the farm (5 in this case), h is the number of turbines over the length of the farm (1 in this case), and R is the distance from which a wind turbine is visible. R has been approximated using data from Bishop (2002). Bishop (2002) determined the threshold for visual impact for the considered wind turbine to be around 4000 meters. The height of the turbine considered by Bishop (2002) (sum of the hub height and rotor radius) is 70 meters. The arc spanned by the height of this turbine at 4000 meters is $\text{atan}\left(\frac{70}{4000}\right) = 0.0155$ radians. Calculating the visual impact threshold for the Vestas V110 turbine, with a hub height of 100 meters results in $R_{110} = 8914\text{m}$ and for the Vestas V66 with hub height of 65 meters $R_{66} = 5600\text{m}$.

From this the VIA can be calculated to be 12.2 km^2 per turbine for V66 turbines and 32.7 km^2 per turbine for V110 turbines. There is a big difference between the impact of a bigger wind turbine and a smaller wind turbine. After correcting for the higher output of the bigger wind turbine, the area affected per kWh/y is almost two times higher for the bigger wind turbine. This is consistent with findings in other research analyzing the visual impact of wind turbines. Tsoutsos et al. (2009) even found that 11 smaller wind turbines were considered to have a smaller impact than one big wind turbine.

The numbers that are found for visual impact are relatively large, owing to the small wind farm size selected. In analyzing the results, connecting a number to this value will help in comparing different designs. The exact numbers, however, are not important, and a more thorough analysis is necessary to be able to say more about the visual impact of wind turbines. This could be done by taking the location of wind farms and the affected area into account and determining how many people are affected. For this research, this was not included in the scope. In this research, the numbers for VIA will be used to compare different outcomes on their desirability to different stakeholders and to analyze the trade-offs between lowering the visual impact of wind turbines and other important criteria.

6.4. Verification of the model

After the simulation model has been defined, the optimization problem is defined, and all data has been input into the model, it needs to be confirmed that the quality of the model and the outcomes is sufficient. Two steps need to be taken before meaningful conclusions can be drawn from the model: verification and validation. During the verification, it is determined whether or not the final model is a correct representation of the mathematical conceptualization. Verification is specifically not meant to check whether or not the results from the model represent the real world. This is done in the validation of the model results, which will be discussed in chapter 8. In this section, the model is verified to correctly represent the conceptual model and to provide a proper translation of theory into a model.

The model was verified in two ways: first, the equations in the model were checked by continuously checking the correctness of the outcomes of the equations. Secondly, the function of the model is checked by looking at expected outcomes.

6.4.1. Verifying the correctness of the outcomes of the equations

The first step in the verification was performed throughout the modeling process. Both the simulation model and the optimization model were continuously checked for correctness. The simulation model was created in a modular way, and all individual elements were checked to perform as expected by checking the values by hand and by trying extreme inputs to test if the equations behaved as expected. First, the demand and grid connection were modeled, followed by wind and PV energy generation. These elements were individually checked. Following this, biomass and storage were added. The model consists of large sets of matrices and vectors. All functioning is automated, but the matrices were checked in every step of the way. Many small (and some bigger) errors were discovered and had to be corrected. After the model had been completed, everything was checked multiple times. Looking at the outcomes can confirm the correct specification of the model.

6.4.2. Verifying the model outcomes: does the simulation model behave as expected?

By looking at the results from the simulation model for many different generation mixes, including PV, Wind, biomass, and storage, the proper functioning of the model was verified. In figure 6.8, the results can be seen to confirm that the model functions as expected: demand and supply are exactly matched. The figure shows the results for a generation mix including 72MW wind energy, 46MW solar energy, and 2MW biomass energy. Biomass is only applied when necessary and energy is imported for shortages and exported for surpluses. A clear daily pattern in PV generation can be observed. Further investigation also showed that the amount of energy generated corresponds precisely to the relative installed capacities and capacity factors.

The energy storage sub-model was also tested. The results are shown in figure 6.9. The energy storage is charged when possible and discharged when necessary. In this run, around 220MW of storage was included. Further investigation showed that the surface beneath the blue line is indeed around 220 MW when maximally discharged.

The different outcomes were also verified to behave as expected. When no generation capacity is installed, land use, CapEx and VIA are zero and LCOE is equal to the average grid electricity price.

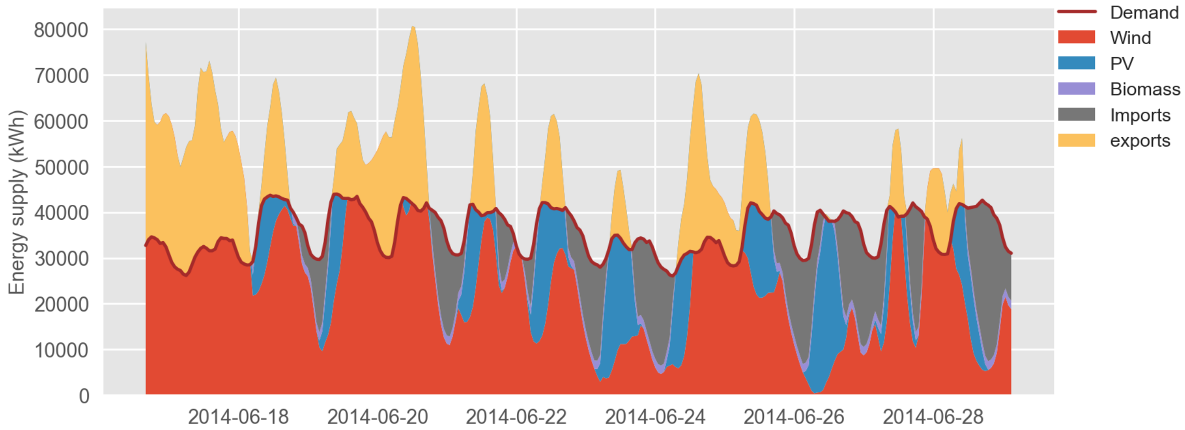

Figure 6.8: Energy generation per method in the simulation model for two random weeks.

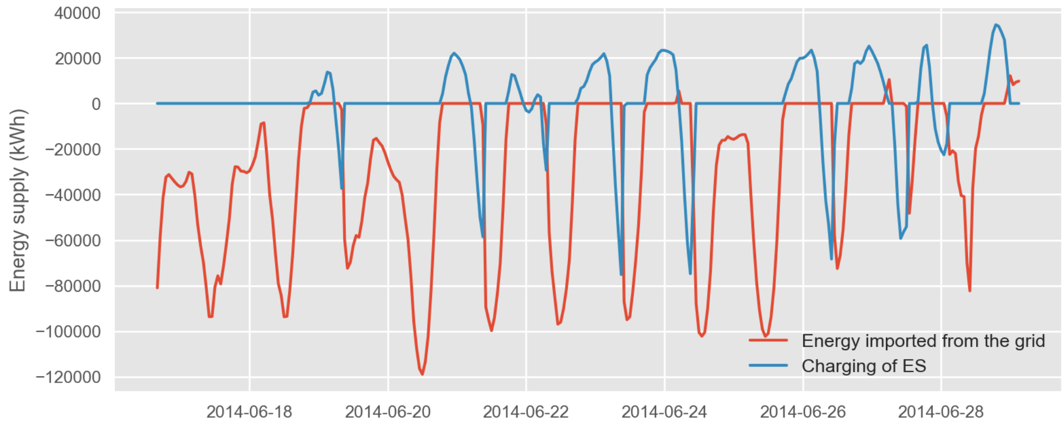

Figure 6.9: Verifying the correct functioning of the energy storage sub-model. A positive value for energy from the grid indicates imports, negative values indicate exports. For energy storage, a positive value indicates charging of the storage, a negative value indicates discharging.

6.4.3. Verifying the optimization outcomes: does the optimization model behave as expected?

The optimization model was also continuously verified. Many different combinations of objectives have been tried to see the effects. If objectives are not conflicting, the optimization will return a set of 3000 identical (Pareto-optimal) solutions, because there will be one optimal solution. The same is true when only one objective was included.

If VIA is minimized as a single objective, as little wind as possible (within the constraints) is included in the generation mix. The opposite was true when only minimizing LCOE. Minimizing only land use will result in full utilization of the available rooftop surface in the region for residential solar panels. These outcomes were all in line with what was expected from the optimizations.

The set of results from the optimization covers the entire decision space, and increasing the number of generations does not alter the results.

From these findings, it was clear that the optimization model also functions as expected. In this research, the aim is to identify the optimal generation mix for different scenarios of CO_2 reduction. These scenarios have not yet been specified. In the next section, the scenarios to be analyzed will be introduced.

6.5. Set-up of the experiments: analyzing the behavior of the system

The goal of this thesis, as formulated in the introduction, is to find the optimal generation mix for a regional energy system. As an input, the desired level of CO_2 reduction (one of the constraints defined in section 5.2.2) is required: reducing emissions by a specific amount is the target and the solution should be optimally suited to reach this target.

The Dutch government has set the target to generate 70% of the consumed energy from RES-E. In our system, this is equivalent to a 70% emissions reduction because most emissions are a result of importing energy, and all energy generated in the region is from a renewable source. Therefore, analyzing the optimal generation mix for a scenario of 70% emission reduction would be very interesting. It would also be interesting to see how the optimal generation mix changes when a higher target is set in the future.

Up to this point, however, there is no information on what the possibilities for CO_2 reductions are in the system: is it even possible to generate enough electricity to save 70% of the emissions without violating any constraint regarding land use, available cropland, and available rooftop surface? Also, there is no information about the behavior of the system if even more emissions are to be prevented. It would be interesting to see how CapEx, LCOE, Land use and VIA increase as the CO_2 targets are set to more ambitious levels: is it attractive to set a higher target or do costs increase exponentially? Answering these questions requires a separate analysis.

The objectives that are included are changed for this section, only to analyze the behavior of the model. CO_2 emissions will be optimized against each of the four individual objectives. Four two-objective optimizations are performed, leading to four two-dimensional plots of the trade-off between emissions and each of the other objectives. From these plots, the possibilities of reducing emissions in the system can be seen: do the optimizations return feasible results that show a reduction of 70% or more of the emissions? Also, from these plots, the trade-off between reducing emissions and the other objectives can be seen: does setting higher targets lead to exponentially higher costs and land use? From this, interesting scenarios of emission reduction can be identified that will be used in obtaining the result.

Figure 6.10 shows the results of the optimizations minimizing CO_2 and Land Use, CapEx, or Visually Impacted Area. Minimization of emissions and LCOE has been provided in appendix E.

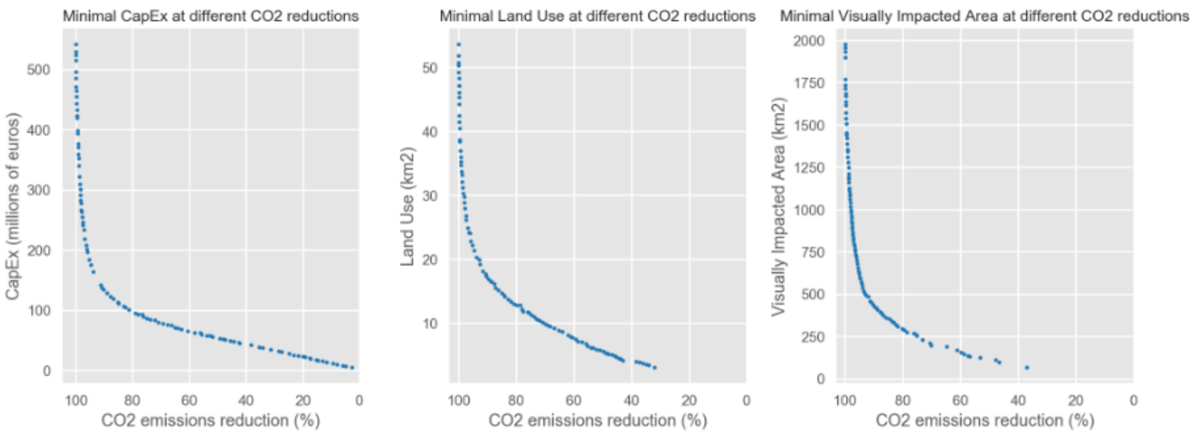

Figure 6.10: Evaluating the trade-off between reducing CO_2 emissions and the other criteria. The reduction in CO_2 emissions compared to the emissions without renewable energy is shown on the X-axis. Land use, CapEx and VIA are represented on the Y-axes.

From the first figure, showing the trade-off between reducing emissions and CapEx, it is already clear that Goeree is able to almost completely eliminate all emissions. The minimal investment that is needed increases linearly until around 80% reduction of emissions is reached. From this point, the effects of intermittency come into play, and a significant amount of overcapacity or energy storage is necessary to be able to fulfill demand.

The same picture can be seen when looking at the second plot showing the trade-off between reducing emissions and land use. Although Goeree is theoretically able to almost fully eliminate any emissions, the required land use increases exponentially above reductions of 80%. When optimizing for minimal land use, it can be seen that no solutions are found that have a lower land use than 3 km^2 (at 32% reduction in emissions). Further investigation showed that the reason for this is that only residential solar is not profitable enough: additional capacity is required to keep the IRR above 3% (which is one of the constraints).

The minimal visual impact from wind turbines is almost zero until a reduction of around 60% is reached. From this observation, it is clear that 60% CO_2 reduction is possible with only one or two wind turbines. If the targets are to reduce emissions by more than 60%, more wind turbines are required to fulfill demand. An extreme increase in the VIA is observed if the targets are higher than 95% reduction in emissions: a considerable overcapacity is required to be able to fulfill demand. Many wind turbines are required, and a minimum area of up to 2000 km^2 is visually impacted, meaning that around five wind turbines are visible from anywhere in Goeree. Bear in mind that this is an optimized situation regarding VIA. If other objectives are also taken into account, the VIA will likely be even higher.

In the next steps of the analysis, several scenarios of CO_2 emissions will be evaluated. Very high reductions in CO_2 emissions are possible in Goeree, as is clear from this section. The first scenario investigates the national targets set by the Dutch government in the climate accord of 2019 of **70% CO_2 reduction**. The second scenario will regard **90% CO_2 reductions**, where the effects of intermittency really come into play. The final scenario aims to investigate the possibility of becoming almost CO_2 neutral with a CO_2 **reduction of 98%**. The reason that 98% reduction is chosen over 100% reduction is that biomass also emits some CO_2. Reducing emissions by 98% means that the system is already almost entirely self-sufficient: only around 0.1 - 1% of the energy is imported (depending on the amount of biomass). Targeting 100% emission reduction means that biomass would be excluded as an energy source, which is not desirable because biomass is the only flexible generation method included in the model. The results for the optimization for these three scenarios will be analyzed in the next chapter.

7

Analysis of the results of the optimization

The previous chapters have defined the simulation model, the optimization problem, and the data input. The model is now fully described and experimentation can begin. This chapter will present the main results of the optimizations for each scenario defined in section 6.5. Analyzing the results of a multi-objective optimization is not straightforward, however. The methods used to analyze the results will be discussed first.

7.1. Methods used to analyze the results of the optimizations

The optimization for each scenario will result in a set of 3000 Pareto-optimal outcomes, as was explained in section 5.5. Each outcome consists of 6 decision variables and four output variables. Because of the large and high dimensional data-set, processing the results is challenging. A structured approach is necessary. The general structure of the analysis is represented in figure 7.1. This approach will now be described in five steps:

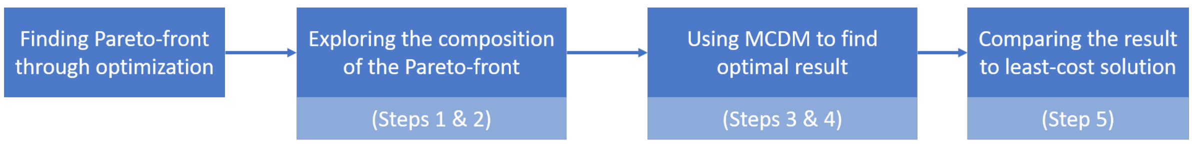

Figure 7.1: Structure of the analysis of the results.

1. **Analyzing the most significant effects of the installed capacities on different criteria.** In this step, the effect of the individual generation methods on the criteria is analyzed: which generation methods lead to cheaper energy? Which generation methods lead to higher land use? This analysis is done by pairwise plotting of the decision variables against the criteria.

2. **Scenario-based trade-off analysis.** In this step, the three sets of outcomes will be analyzed to investigate the general trade-offs between the different objectives. From this, for instance, it can be determined how much it will cost to decrease land use by a certain percentage. Looking at the trade-offs can be done by creating pairwise plots for the objectives.

3. **Optimal generation mix for different stakeholders.** Each optimization outcome receives a score for each actor that is calculated by using the TOPSIS method, which is explained below. A score of one means that it is the most desirable for the actor in the given scenario. Zero indicates that it is the least desirable. The optimal generation mix for each actor is investigated. From this analysis, an ideal outcome is identified for each scenario that satisfies each actor as much as possible: the total average optimal result. This solution is further investigated in the next step.

4. **Analyzing the ideal outcomes for each scenario.** The previous step identifies one optimal result for each scenario that satisfies each actor as much as possible. In this step, the total average optimal result for each scenario is further investigated.

5. **Comparing the total average optimal result to the cost-optimal solution** is the final step in analyzing the results. From this, the added value of performing a multi-objective optimization, and the differences to a cost-optimal solution will be clear.

Having introduced each step, the following sections will show the results from each step of the analysis. Only the most interesting results will be shown; the remaining plots will be shown in the appendix.

7.2. Step 1: Analysis of the most significant effects of the installed capacities on different criteria

After the optimizations for each scenario are performed, the results are investigated. This section evaluates the relations between the installed capacities and the different criteria. Several very interesting observations can be made from this which are only possible after performing a multi-objective optimization.

This analysis is done by examining pairwise plots for the decision variables and the criteria. Please note that the pairwise plots do not have matching x- and y-axes. The choice is made to use different axes because the most important conclusions from this section are the relationships between the different variables, not the absolute values of the variables.

Figure 7.2 shows the total capital expenditure related to the share of wind power in the generation mix. Each point in the scatter plot represents one of the three thousand outcomes. It is clear that, up to a certain point, more wind power reduces cost because it is relatively cheap. Above a wind power share of around 60%, however, the total CapEx rises in the second and third scenarios. This is because at higher levels of CO_2 reduction, a significant overcapacity of wind power is needed if wind power comprises over 60% of the generation mix (due to intermittency effects). This leads to higher CapEx.

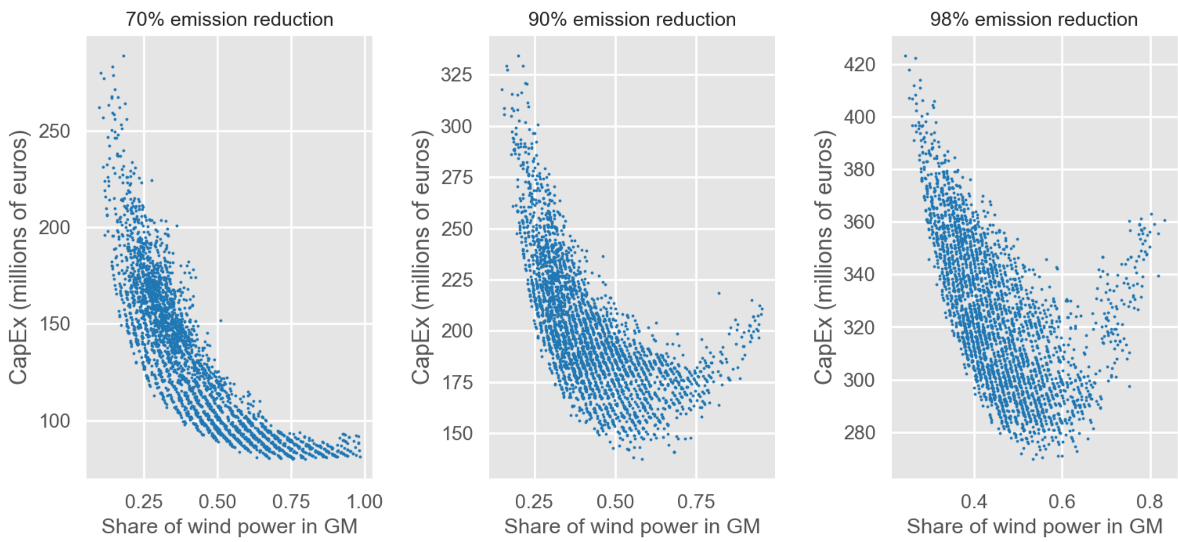

Figure 7.2: Effect of a higher percentage wind power in the generation mix on the capital expenditure. The share of wind power is on the x-axis, the total capital expenditure is on the y-axis.

Another very interesting result from analyzing the Pareto front is the effect that energy storage has on land use. This is shown in figure 7.3. At 70% emission reduction, storage has no significant effect on land use, and most solutions do not include any storage in the generation mix. At 90% and 98% emission reduction, the results are vastly different: including storage can significantly reduce the required land. It can be seen that no solutions exist that have no storage and require little land. When more money is invested in energy storage, land requirements can be reduced by up to 50% in the second scenario.

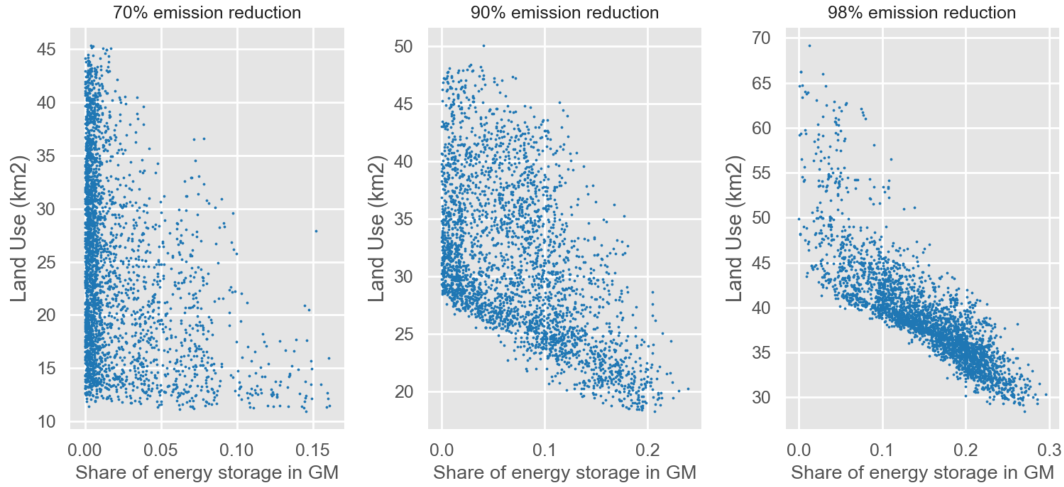

Figure 7.3: How the share of storage in the generation mix affects land use in three different scenarios of CO_2 reduction.

7.2.1. Conclusions from analyzing the effects of the generation mix on the criteria

From this section, it is clear that there is an optimal share for wind power in the generation mix when only CapEx is considered, and that storage can reduce the required land to produce enough electricity. The full results are presented in appendix E.2.

The most important observation, however, from this section is that performing a multi-objective optimization can lead to more insight into the functioning of the system and the effect of composing the generation mix in different ways because multiple outcomes are presented instead of one optimal outcome. Especially the effect of storage on land use would not have been visible otherwise. The next section will show another benefit of performing a multi-objective optimization: the trade-offs between different criteria can be visualized.

7.3. Step 2: analysis of the trade-off between different criteria

Having identified some relevant relations between generation technologies and the different criteria, the trade-offs between different criteria are analyzed. The full outcomes can be found in appendix E.3.

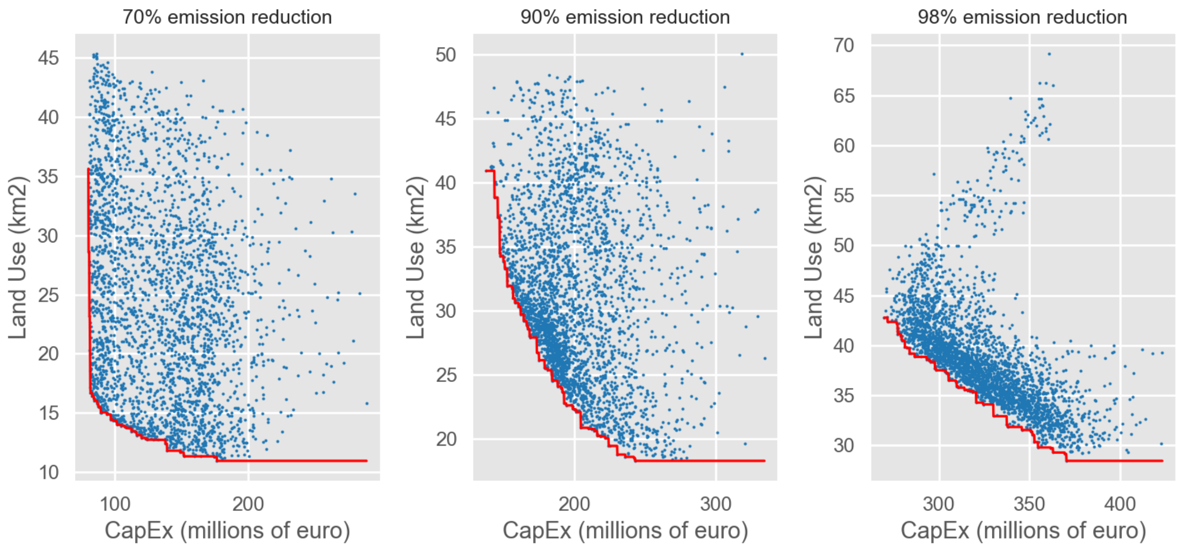

Figure 7.4: Evaluating the trade-off between CapEx and land use for different scenario's of CO_2 reduction. The Pareto-front for these specific criteria is shown by a red line.

Figure 7.4 shows the results plotted for CapEx and land use. As can be seen, CapEx and land use are bigger for higher reductions. For every scenario, there is a trade-off between capital expenditure and land use: a 40%-50% reduction in land use requires a high investment. For the emissions reduction of 70%, around twice the investment is necessary to reduce land use by 40%. This is a high price to pay.

If a 90% CO_2 reduction is the goal, the trade-off is more significant. The necessary land can be reduced from 40 km^2 (which is a third of the available land) to 20 km^2 by investing 30% more. An important consequence of this observation is that by only optimizing for CapEx, one would receive a solution at the extreme end of the Pareto front. This would lead to high amounts of land use: optimizing for a single objective leads to finding extreme solutions that may not be desirable if other criteria are considered.

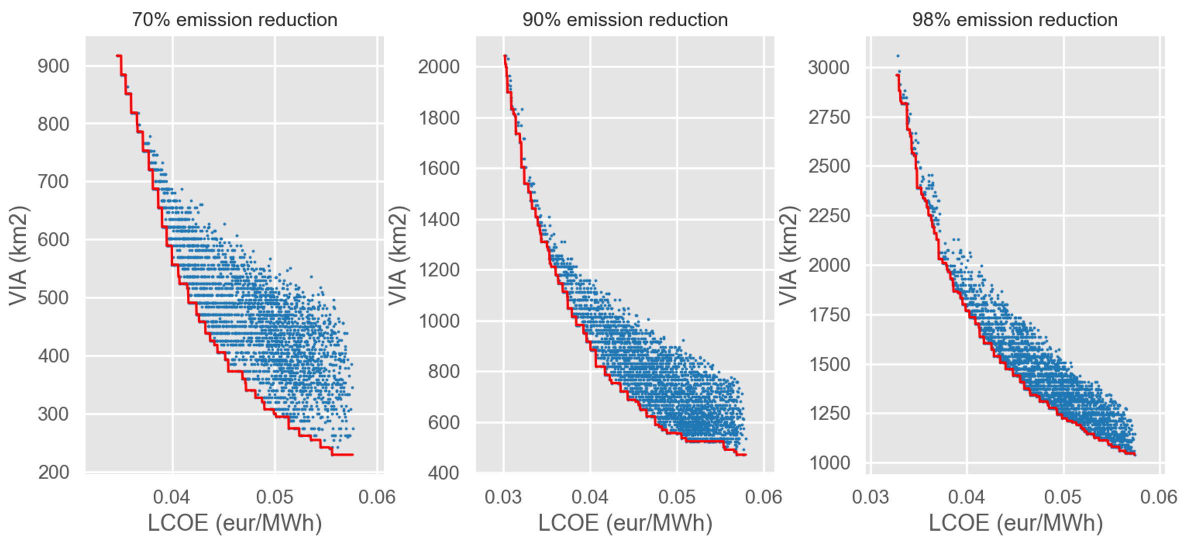

Figure 7.5: Evaluating the trade-off between a low LCOE and the visually impacted area: the market will converge to a high amount of large wind turbines because of lower prices, leading to a high visual impact.

In figure 7.5, the trade-off between a low LCOE and a low Visually Impacted Area (VIA) is shown. The outcomes show that a significant trade-off between LCOE and VIA exists. A low LCOE (and therefore a high IRR) is achieved by installing many big wind turbines, leading to high VIA. This may indicate that the market will focus on building wind turbines and without providing other incentives to investors, the visual impact may be very high.

7.3.1. Conclusion from the trade-off analysis

From this section, the main conclusion that can be drawn is that there is a clear trade-off between the different criteria. By choosing an ideal scenario for one criterion, serious sacrifices on some other areas are made. For instance, choosing to minimize LCOE will result in high shares of wind power. This will have detrimental effects on the visual impact caused by the power system. There is also a clear trade-off between CapEx and land use: optimizing only for minimal CapEx results in very high land use, which is not desirable. This observation leads to the conclusion that a balanced generation mix is best in order to perform acceptably on all criteria. In the next section, a multi-actor analysis is performed to find this ideal generation mix.

7.4. Step 3: analysis of the results from a multi-actor perspective

From the previous sections, it is clear that the composition of the generation mix seriously influences the criteria and that there is a trade-off between the different criteria: no single optimal solution exists. To be able to find an optimal solution that satisfies all actors as much as possible, the results are analyzed using MCDM from a multi-actor perspective. The solutions will be evaluated based on their desirability to different actors, and a final optimal solution for each scenario will be presented. First, a reflection on the involved actors and their preferences is provided.

7.4.1. Involved actors and preferences

In chapter 2.2, the most important actor groups were identified. In table 2.5, the interests of the actor groups regarding the criteria used in this research are explained. This table is repeated here for clarity as table 7.1.

Table 7.1: Evaluating the interests of the three main actor groups regarding the criteria that are included in this research.

Min/max	**LCOE** min	**CapEx** min	**Land use** min	**Visual impact** min
Governments	√		√	√
Investors	√	√		
Local residents				√
Consumers	√			

From the results above, it is not directly clear which results are most desirable to which actors. A ranking of the outcomes for each actor is necessary. This ranking is obtained with a Multi-Criteria Decision-Making (MCDM) method called TOPSIS.

7.4.2. Introducing TOPSIS, a Multi-Criteria Decision Making method

To be able to obtain a ranking for the alternatives, any MCDM method could be used. This research uses the well-known Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), which was first proposed by Hwang (1981). The TOPSIS method ranks the alternatives based on the geometrical distance to the ideal point. This method was chosen because the method is simple, and it can measure the relative performance of all alternatives in a scalar value. Also, TOPSIS performs well regarding rank reversal (Zanakis et al., 1998), and it does not require pairwise comparison. Methods requiring pairwise comparison, such as Analytical Hierarchy Process (AHP), require specific input of the involved actors, which is beyond the scope of this research. Shih et al. (2007) presented a simple method of combining the preferences of multiple actors to allow for group decision making, which will be used in this research. The process for TOPSIS can be described as follows:

Step 1 is to construct the decision matrix consisting of the values for each of the four criteria for each alternative: $D_{\mathrm{ij}}, \quad \forall i \in n, \forall j \in M$. Where M is the number of criteria (which is 4), and n is the number of alternatives (which is 3000 after the optimization).

Step 2 is to create a normalized decision matrix with the normalized values (R). A simple linear normalization is applied. In the equation below, $D_{\mathrm{max,j}}$ represents the maximum value for criterion j out of the complete set of solutions. $D_{\mathrm{min,j}}$ represents the minimum value for criterion j. :

$$R_{\mathrm{ij}} = \frac{D_{\mathrm{ij}} - D_{\mathrm{min,\,j}}}{D_{\mathrm{max,j}} - D_{\mathrm{min,\,j}}} \quad \forall i \in n, \forall j \in M \tag{7.1}$$

Step 3 is to define the weighted normalized decision matrix for each actor (V). The weights are determined based on table 2.5. Criteria important to one actor group are awarded a weight of 1. If a criterion is not important to a specific actor group, the weight is 0. Because of a lack of specific information about the preferences of the actors, further specification of the weights is not possible. In the equation below, A represents the set of the four actor groups.

$$V_{\mathrm{ij,\,a}} = w_{\mathrm{j,a}} \cdot R_{\mathrm{ij}} \quad \forall i \in n, \forall j \in M, \forall a \in A \tag{7.2}$$

Step 4 is to find the positive ideal solution ($A^{+}{}_{\mathrm{a}}$) and the negative ideal solution ($A^{-}{}_{\mathrm{a}}$) for each actor. The positive ideal solution is a vector with the optimal values with the outcome set for each criterion. The negative ideal solution is a vector with all of the *worst* values for each criterion. In this research, all criteria are minimized. In the equation below, $v_{\mathrm{j,a}}$ represents the vector of all weighed outcomes on criterion j for actor a. The total number of criteria is represented by the size of set M ($|M|$). $A^{+}{}_{\mathrm{a}}$ and $A^{-}{}_{\mathrm{a}}$ can be calculated as:

$$A^{+}{}_{\mathrm{a}} = [min(v_{1,\mathrm{a}}), min(v_{2,\mathrm{a}}), ..., min(v_{|\mathrm{M}|,\mathrm{a}})] \quad \forall a \in A \tag{7.3}$$

$$A^{+}{}_{\mathrm{a}} = [max(v_{1,\mathrm{a}}), max(v_{2,\mathrm{a}}), ..., max(v_{|\mathrm{M}|,\mathrm{a}})] \quad \forall a \in A \tag{7.4}$$

Step 5 is to derive the positive distance vector (S^{+}) and the negative distance vector (S^{-}) for each alternative for each actor. Which gives the Euclidean distance between each alternative and the ideal alternatives (A^{+} and A^{-}).

$$S^{+}{}_{\mathrm{i,a}} = (\sum_{k=1}^{|M|} (A^{+}{}_{\mathrm{k}} \cdot V_{\mathrm{i,k}})^2)^{\frac{1}{2}} \quad \forall i \in n, \forall a \in A \tag{7.5}$$

$$S^{-}{}_{\mathrm{i,a}} = (\sum_{k=1}^{|M|} (A^{-}{}_{\mathrm{k}} \cdot V_{\mathrm{i,k}})^2)^{\frac{1}{2}} \quad \forall i \in n, \forall a \in A \tag{7.6}$$

Step 6 is to determine the so-called normalized Coefficient of Closeness (CC) for each alternative for each actor. To do this, first the absolute Coefficient of Closeness (CoCl) is calculated.

$$\mathrm{CoCl}_{\mathrm{i,a}} = \frac{S^{+}{}_{\mathrm{i,a}}}{S^{+}{}_{\mathrm{i}} + S^{-}{}_{\mathrm{i}}} \quad \forall i \in n, \forall a \in A \tag{7.7}$$

After calculating the coefficient of closeness, it is normalized through linear normalization. The absolute value is not that relevant to this research, the main interest is the ranking of the criteria and comparing the desirability of the criteria for each actor. Therefore, normalizing the coefficient of closeness gives the most representative results. The normalized coefficient of closeness (CC) is the final value that will be analyzed. A normalized coefficient of closeness that is 1 means that the alternative is the closest to the ideal solution for the specified actor.

$$\mathrm{CC}_{\mathrm{i,a}} = \frac{\mathrm{CoCl}_{\mathrm{i,a}} - \mathrm{CoCl}_{\mathrm{min,a}}}{\mathrm{CoCl}_{\mathrm{max,a}} - \mathrm{CoCl}_{\mathrm{min,a}}} \quad \forall i \in n, \forall a \in A \tag{7.8}$$

Step 7 is the final step. Each alternative now has a value for CC for each actor. To combine the preferences of the actors, the method proposed by Shih et al. (2007) is used. The geometric mean of each CC for all actors is calculated to be able to define a total coefficient of closeness. In the equations below, $|A|$ represents the size (cardinality) of the set of actors A.

$$\mathrm{CC}_{\mathrm{i,\ total}} = (\prod_{a \in A} \mathrm{CC}_{\mathrm{i,\ a}})^{\frac{1}{|A|}} \quad \forall i \in n \tag{7.9}$$

One more value is defined for each alternative: the $maximin_{\mathrm{i}}$ value ($\forall i \in n$). For each alternative, the $maximin_{\mathrm{i}}$ value is defined by taking the minimum CC of all the actors. The solution that maximizes the minimal satisfaction for all actors gets the highest score.

$$maximin_{\mathrm{i}} = \min \mathrm{CC}_{\mathrm{i}} \quad \forall i \in n \tag{7.10}$$

Where CC_{i} is the vector of all the CC scores of the different actors for an alternative i:

$$\mathrm{CC}_{\mathrm{i}} = \{\mathrm{CC}_{\mathrm{i,\ a_k}}\}_{\mathrm{k}=1}^{|A|} \quad \forall i \in n \tag{7.11}$$

Having described the methods used to come up with a ranking for each actor and two aggregate rankings, the results are now discussed. The results are discussed based on parallel coordinates plots with highlighted solutions. This method of visualizing the results, requires some explanation.

7.4.3. Explanation of the parallel coordinates diagrams

Set of outcomes has many dimensions. Both the decision variables, the criteria, and the relative scores for each actor need to be analyzed. To analyze this high dimensional data set, Coello et al. (2005) suggests using a parallel coordinates plot. This method will also be employed in this research. The first parallel coordinates plot is shown in figure 7.6. Each line that crosses the parallel axes from left to right represents one of the outcomes of the optimization. Each of the parallel (vertical) axes represents one of the elements from the generation mix or one of the outcomes. From left to right, the variables shown are:

- Wind: Share of the CapEx of wind power in the total CapEx of the generation mix
- PV: Share of the CapEx of solar power in the total CapEx of the generation mix
- Biomass: Share of the CapEx of biomass power in the total CapEx of the generation mix
- Storage: Share of the CapEx of energy storage in the total CapEx of the generation mix
- LCOE: Levelized Cost Of Electricity (in €/MWh)
- Land use: the land used in generating electricity (in km^2)
- Capex: the capital expenditure of investing in the power system (in millions of euros)
- VIA: the area that is visually impacted by wind turbines (in km^2).
- Gov't: the normalized TOPSIS CC score for the governments
- Investors: the normalized TOPSIS CC score for the investors
- Consumers: the normalized TOPSIS CC score for the consumers
- Residents: the normalized TOPSIS CC score for the local residents
- Total_pref: the total averaged preference scores for all actors
- maximin: the value of the TOPSIS CC score of the actor that is least satisfied for each outcome

The CC scores for each outcome have been represented as well as the total average CC and maximin. The sections below will evaluate the optimal generation mix for different actors in each scenario. Not all actors are discussed. Local residents and consumers have a one-dimensional preference. Local residents intend to minimize VIA, leading to costly results with little wind power. Consumers favor solutions with the lowest LCOE, leading to high land use and high VIA. Governments and investors have a more diverse set of interests, and analyzing these results will be more interesting.

7.4.4. Analyzing the results for scenario 1: 70% emission reduction

For the first scenario, several interesting observations can be made. Figure 7.6 shows the optimal results for the investors. The investors are interested in building mainly wind turbines. Almost no solar, biomass, or storage is included in the generation mix, resulting in the generation mix with the lowest LCOE and CapEx. The result is that the VIA will be very high, and local residents will not be happy with this solution. The investors are aligned with the consumers: both want to lower the LCOE by building more wind turbines.

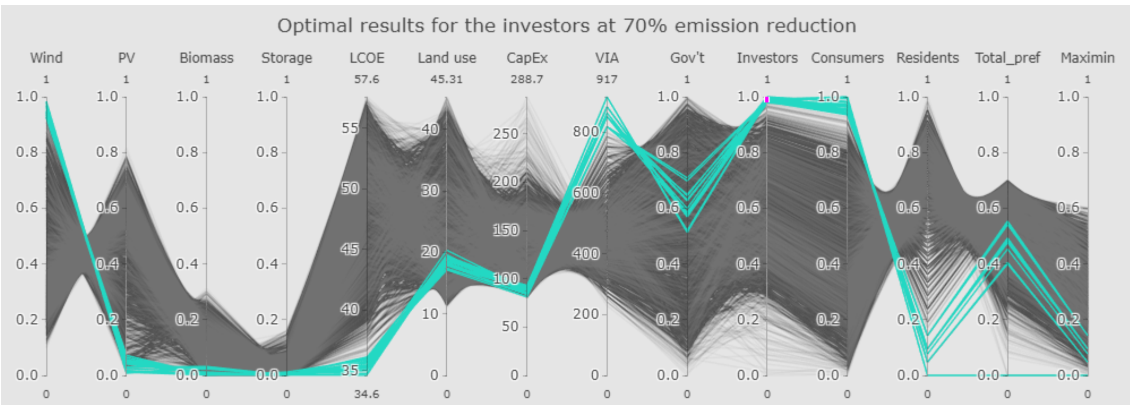

Figure 7.6: Parallel coordinates diagram showing the optimal results for investors for the optimization with 70% emission reduction. The blue lines are the outcomes in the optimal 0.5% for investors. The grey lines are not within this optimal 0.5%.

The optimal situation for the governments shown in figure 7.7, however, paints a different picture. Governments favor a more balanced generation mix, and relatively large investments in solar are required. This will limit the land use to be around 15 km^2. VIA will also be limited, but it is still high. It can be seen that the local residents are not very satisfied with the solution. Also, the result is not optimal for investors and consumers. The preferences of the governments do present a good match with the total average CC: it is a good balance between the different criteria.

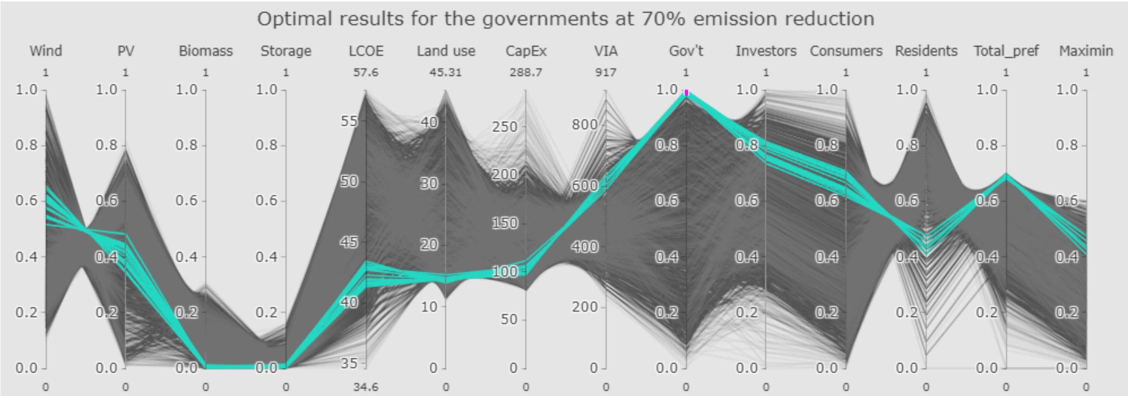

Figure 7.7: Parallel coordinates diagram showing the optimal results for governments for 70% emission reduction. The blue lines are the outcomes in the optimal 0.5% for the governments. The grey lines are not within this optimal 0.5%.

When looking at the total average CC for all actors in figure 7.8, it is clear that for the 70% scenario, this indeed matches the preferences of the governments. The highest total average CC is achieved when most investments go towards wind and solar (60% wind, 40% solar). The results seem to be well balanced across all criteria. The VIA is still relatively high, however. This results in a low satisfaction for the local residents, leading to a lower value for the maximin criterion. Some solutions, which include less wind power, perform better on maximin, because the residents are more satisfied.

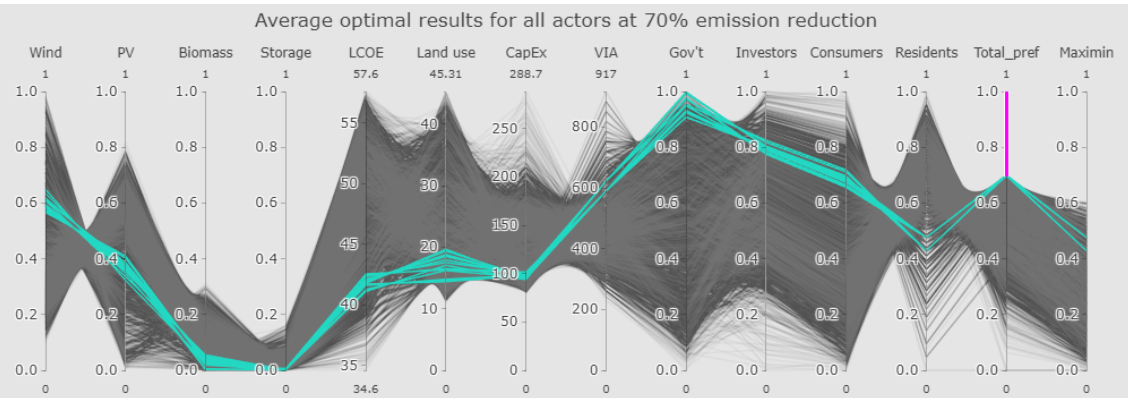

Figure 7.8: Parallel coordinates diagram showing the optimal results averaged for all actors for the optimization with 70% emission reduction. The blue lines are the outcomes in the optimal 0.5%. The grey lines are not within this optimal 0.5%.

Figure 7.9 shows the solutions which perform best on the maximin criterion. These results, however, lead to significantly lower satisfaction for governments and investors, two important actor groups. Therefore, the total average optimal solution is concluded to provide the ideal balance in preferences. If the region considered has a particularly vocal group of residents protesting wind turbines, one could consider moving towards a solution that is more satisfactory for the residents.

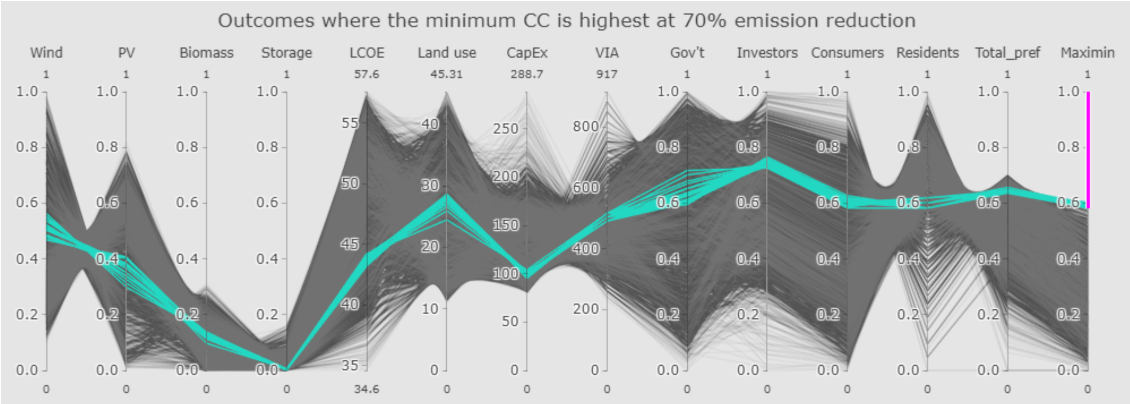

Figure 7.9: Parallel coordinates diagram showing the optimal results for the maximin criterion (least dissatisfaction) for 70% emission reduction. The blue lines are the outcomes in the optimal 0.5%. The grey lines are not within this optimal 0.5%.

7.4.5. Analyzing the results for scenario 2: 90% emission reduction

For the second scenario, the results are also very interesting. There is a clear conflict between the desires of the different actor groups. Figure 7.10 shows the results optimal to the investors. Interestingly, and in contrast with the first scenario, some solar is included in the generation mix. A combination of biomass and solar power makes up about 25% of the generation mix. The rest is made up of wind energy. Again, no storage is included. The results are not optimal for the residents and governments.

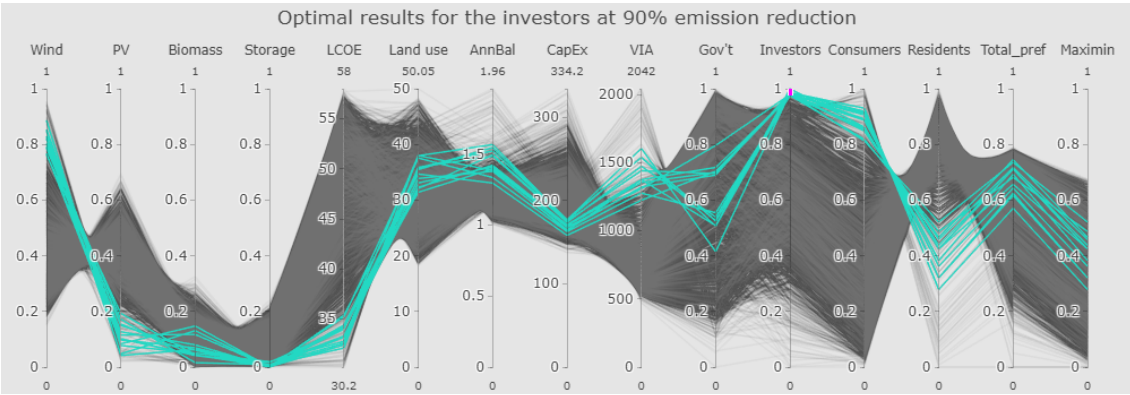

Figure 7.10: Parallel coordinates diagram showing the optimal results for investors for the optimization with 90% emission reduction. The blue lines are the outcomes in the optimal 0.5% for investors. The grey lines are not within this optimal 0.5%.

Figure 7.11 shows the optimal situation for the governments. The investors, consumers, and residents are all not very satisfied with the results. The optimal results for the governments include around 10% of energy storage. This is an interesting contrast to the ideal situation for the investors, which does not include storage. The energy price, however, is relatively high.

The total average optimal solutions for all actors are shown in figure 7.12. Around 65% percent of the generation mix consists of wind turbines. In contrast to the optimal result for governments, energy storage is left out in favor of biomass. CapEx is relatively low. Land use is average at around 30 km^2. This seems like a good compromise on the relevant criteria and also scores well on the maximin criterion. Therefore, it is concluded that this represents the best solution in this scenario for all actors.

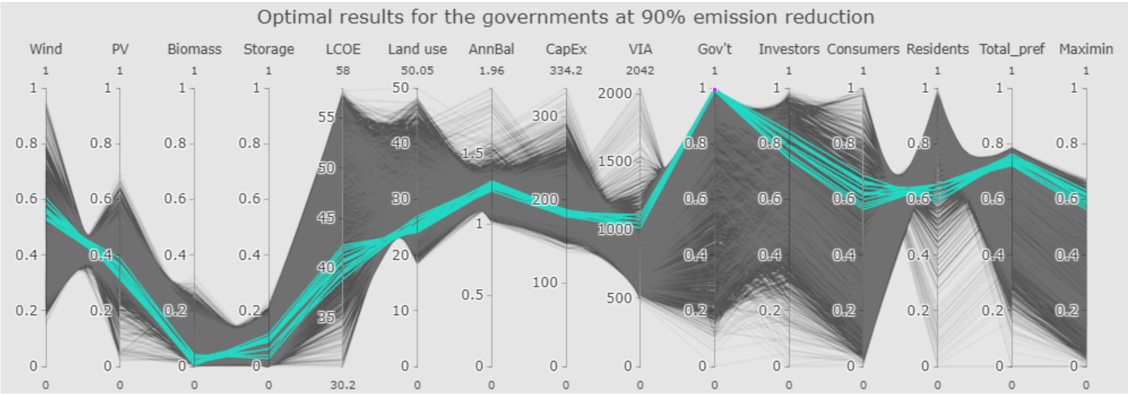

Figure 7.11: Parallel coordinates diagram showing the optimal results for governments for 90% emission reduction. The blue lines are the outcomes in the optimal 0.5% for the governments. The grey lines are not within this optimal 0.5%.

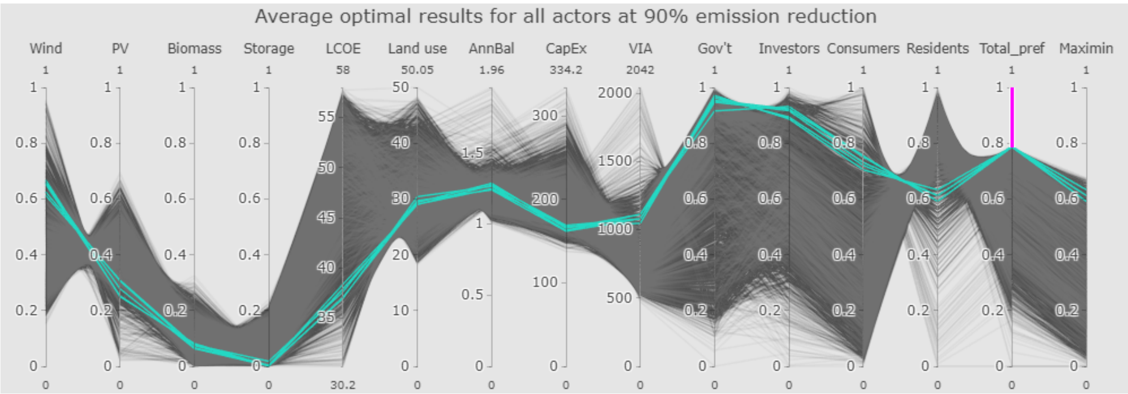

Figure 7.12: Parallel coordinates diagram showing the optimal results averaged for all actors for the optimization with 90% emission reduction. The blue lines are the outcomes in the optimal 0.5%. The grey lines are not within this optimal 0.5%.

7.4.6. Analyzing the results for scenario 3: 98% emission reduction

Finally, the third scenario with 98% emission reduction is considered. For the investors, around 70% wind power seems to be optimal, as is seen in figure 7.13. Again, the investors do not have a preference to include storage, and local residents negatively judge the optimal results for investors because of the large number of wind turbines included in the generation mix resulting in high VIA. The governments also disagree: land use is relatively high in the ideal scenario for the investors.

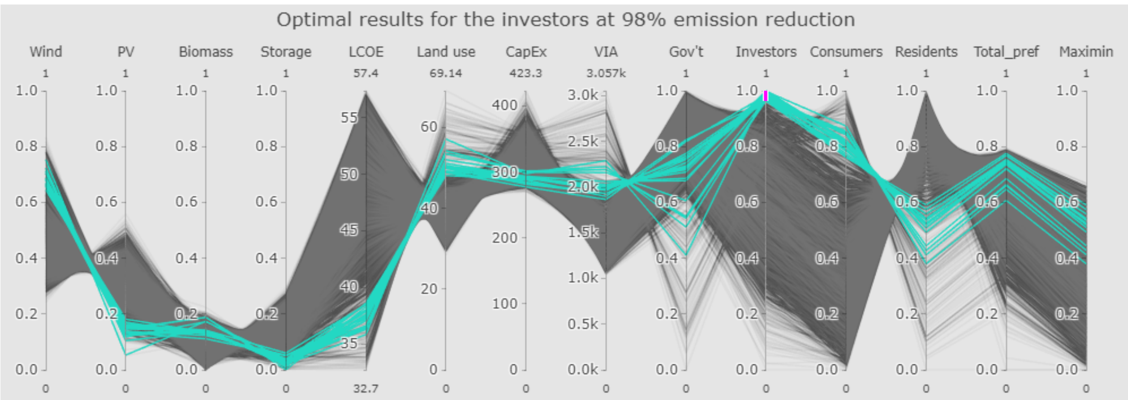

Figure 7.13: Parallel coordinates diagram showing the optimal results for investors for the optimization with 98% emission reduction. The blue lines are the outcomes in the optimal 0.5% for investors. The grey lines are not within this optimal 0.5%.

The governments, similar to previous scenarios, favor a balanced generation mix as can be seen from figure 7.14. Although this is not an interest of the governments, CapEx is quite low in this solution. The consumers are most dissatisfied with this solution: the energy price is too high. The total average optimal solution may provide a better solution.

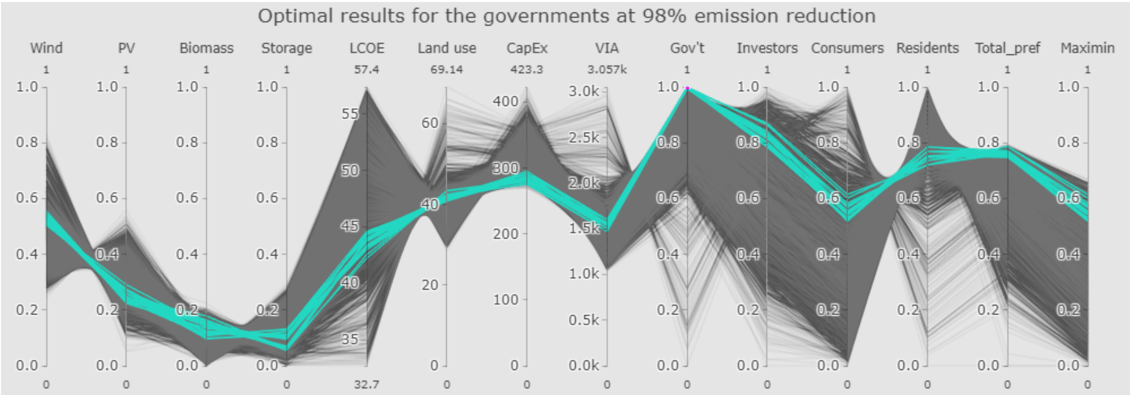

Figure 7.14: Parallel coordinates diagram showing the optimal results for governments for 98% emission reduction. The blue lines are the outcomes in the optimal 0.5% for the governments. The grey lines are not within this optimal 0.5%.

The total average optimal solutions are shown in figure 7.15. Again, a balanced generation mix is favored. CapEx is as low as possible (271 million euros), and around 45km^2 is necessary for energy production. The investors and governments are quite satisfied with the solution. The consumers and the residents are not as satisfied with the solution. Since the performance on the maximin criterion is also almost optimal, it is concluded that this is quite close to the best generation mix considering the preferences of all actors.

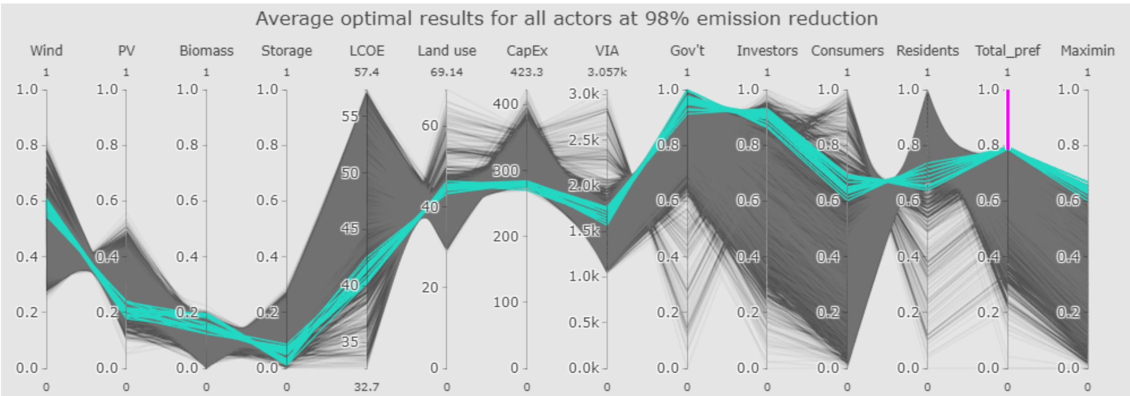

Figure 7.15: Parallel coordinates diagram showing the total average optimal results for 98% emission reduction. The blue lines are the outcomes in the optimal 0.5% for the governments. The grey lines are not within this optimal 0.5%.

7.4.7. Conclusions from analyzing the outcomes from a multi-actor perspective

In this section, all outcomes for the three scenarios of emission reduction are evaluated based on the preferences of different actors. It is concluded that the combined total average preference of all actors provides a good indication of the ideal generation mix in each scenario. From now on, this will be called the total average optimal solution. The total average optimal generation mix for each scenario is further investigated in the next section.

Although the total average optimal generation mix is a representative way of finding one optimal result, it needs to be pointed out that reducing all alternatives to one optimal solution is a simplified representation of reality. It cannot be said that this is the 'best' solution. Having found the complete set of optimal designs, a lot of knowledge has been gained about the trade-offs to be made in selecting an optimal generation mix. Presenting only one solution to decision-makers will result in all this knowledge being lost. A model is ideally used to foster learning instead of providing one optimal solution (Lempert, 2019). If the aim of this thesis were actually to provide direct decision support, the results would not be aggregated to one result: a set of possible solutions could be used as a basis for discussion with and between decision-makers. All solutions are optimal in some way, and the actual best design will depend on actor preferences and contextual factors. The total average optimal result is an example of what a well-balanced generation mix may look like and will be further analyzed in the next section.

7.5. Step 4: analysis of the total average optimal results for all actors

The total average optimal results are analyzed further in this section. Table 7.2 shows the final values for the four most important outcomes. It can be seen that the price of electricity will be more or less consistent for the three scenarios. CapEx, land use, and VIA all increase significantly in each scenario.

Table 7.2: Final total optimal results (averaged for all actors) for the four most important criteria.

Scenario:	LCOE (€/kWh)	CapEx (millions of €)	Land Use (km^2)	VIA (km^2)
1: 70% reduction	0.041	94	17.1	621
2: 90% reduction	0.037	157	30.8	1080
3: 98% reduction	0.041	271	45.4	1636

Figure 7.16 shows the composition of the optimal generation mix. Wind energy makes up the largest part of the generation mix in each scenario. For the first and second scenarios, most of the remaining power is provided by solar panels. When almost all emissions need to be avoided, however, more biomass (flexible generation) is required to be able to deal with the intermittency issues. Interestingly, almost no storage is included, even in the third scenario: the cost of storage is too high to weigh up to the benefits in land use. The required investment increases significantly: if emissions are reduced from 90% to 98%, almost twice the investment is required. This indicates that a significant overcapacity is required to prevent shortages in times of no sun or wind.

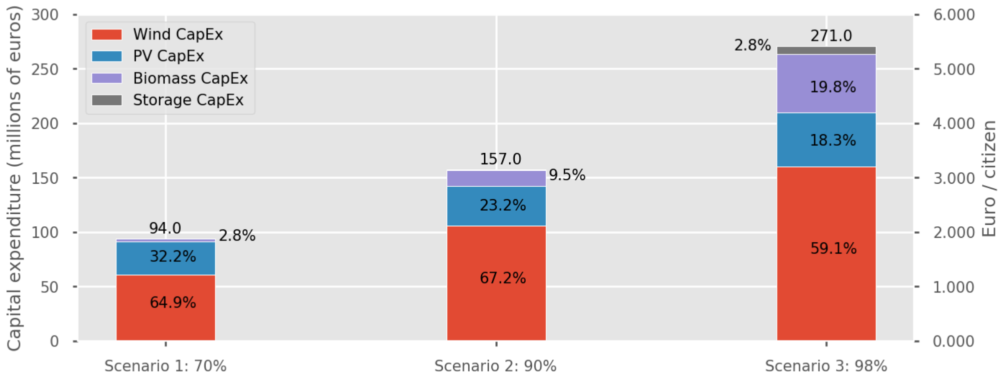

Figure 7.16: Investment cost per technology in the total average optimal results. On the left axis is the total investment. On the right axis is the required investment per citizen in Goeree.

Mainly large wind turbines and utility-scale solar make up the generation mix, as is shown in figure 7.17. The benefits of smaller wind turbines (less land use and VIA) and residential solar (less land use) do not weigh up to the cost of these generation methods. In the third scenario, 100MW of installed wind capacity (50 big turbines) is necessary. This results in a very high VIA, as was shown in table 7.2. In the third scenario, 19MWh of energy storage is included. To put this into perspective: this is only enough to fulfill the average demand of 38MW for half an hour.

Figure 7.18 shows the total land use in each scenario. The required land increases threefold from scenario 1 to scenario 3. The third scenario requires 45 km^2 of land. This means that almost 35% of all available land (130km^2) needs to be used for energy generation. Wind turbines use the highest amount of land, and utility-scale solar has a low land requirement.

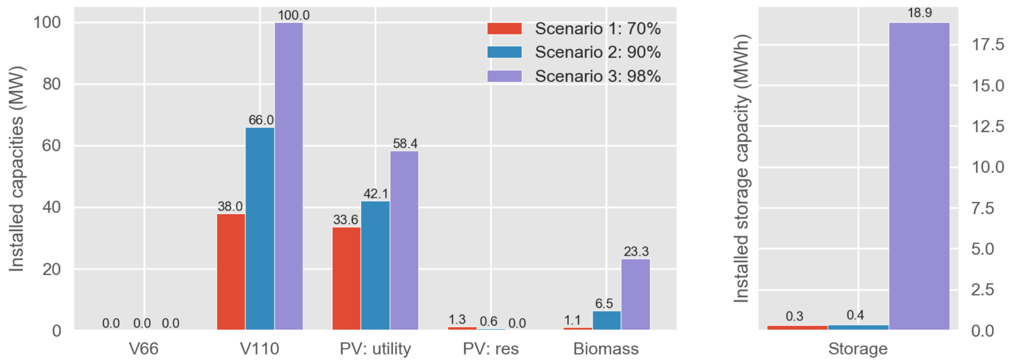

Figure 7.17: The installed capacities for each generation method in the total average optimal solution for each scenario.

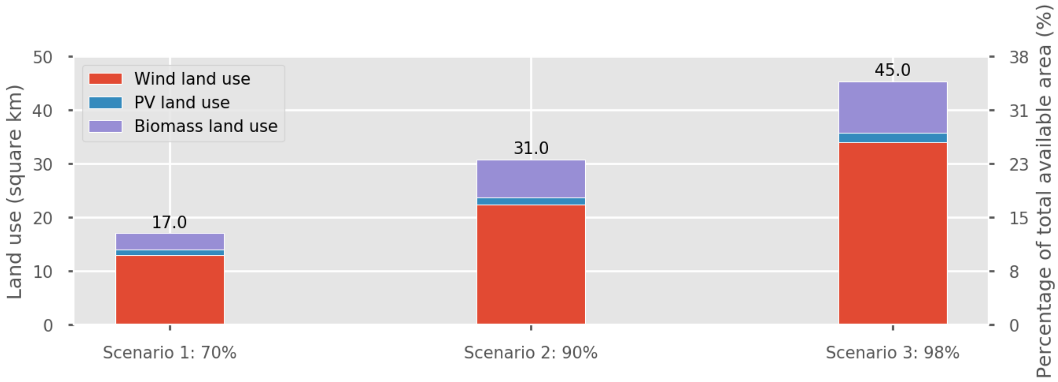

Figure 7.18: The required land use in each scenario. The left axis shows the total required land. The right axis shows the percentage of required land compared to the total available land.

Finally, the total yearly output of energy is shown in figure 7.19. From the left figure, showing the total energy output for each scenario, several observations can be made. In the first scenario, generation is about equal to total demand: not much overcapacity is required. In the second and third scenario, significantly more energy is produced than is used in the region. In the third scenario, more than 45% of the generated energy is exported to outside of the region.

The right figure shows the relative output. In the first scenario, almost 30% of the energy is imported. This is to cover periods with low wind and sun and when biomass is not enough to fulfill demand. Only 0.2% is imported in the third scenario, compared to 7% in the second scenario. Wind power has the most significant share in the output. Especially in the third scenario, a high reliance on wind power is visible. 84% of the energy is generated by wind turbines. This may be a problem if wind speeds are lower than expected.

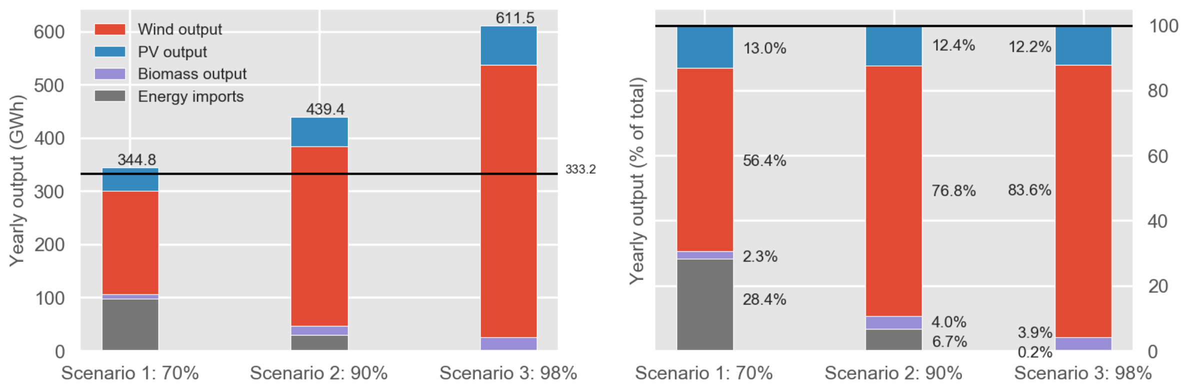

Figure 7.19: Total yearly output per generation method for each scenario. The total energy demand in the region is shown by the black line at 333 GWh. The left figure shows the absolute output and the right figure shows the output as a percentage of the total.

7.6. Step 5: comparing the results to the cost-optimal result

Comparing the solution to a cost-optimal solution is an important final step. It was determined in chapter 2.3 that land use and visual impact should be taken into account in the design of a regional energy system. To see the influence of including these objectives, it should be compared to a cost-optimal solution. As was seen in chapter 3, most studies investigating the optimal generation mix minimize Total Annual Cost (TAC). Therefore, to compare the results, the outcomes with minimal TAC are selected from the Pareto-front. The formula for TAC was presented in equation 4.16. Apart from the cost-optimal solution, the total average result is also compared to the optimal situation for investors. This is interesting because the solution which is regarded to be optimal by the investors represents the solution to which the market will likely converge without intervention. The comparison is shown in figure 7.20. The results on the four different criteria are compared to the average optimal result in table 7.3. From the differences in the preference score, it can be seen that the cost-optimal results and the results optimal for the investors are significantly less desirable than the total average optimal results found in this study.

First, the cost-optimal results are compared to the optimal result found in this study, after which the outcomes optimal to investors are discussed.

The total annual costs for the cost-optimal solutions are a bit lower than for the solution found in this chapter. For the first scenario, only wind is included, resulting in a significant increase in VIA compared to the answers found in this research. In the second and third scenario, a more balanced generation mix is required to be able to balance supply and demand due to the intermittency effects. In the second scenario (90% reduction), the cost-optimal solution uses more biomass and less solar and wind resulting in higher land use (34% higher). The results also show that LCOE is 10% higher in this case because generating energy from biomass is quite expensive.

In the third scenario, the least-cost solution found is quite similar to the results found in this study. More biomass and slightly more storage are included. The least-cost solution requires less solar power and performs comparably on all four criteria compared to the most desirable solution. This indicates that the costs of decreasing land use and visual impact further are too high to be desirable.

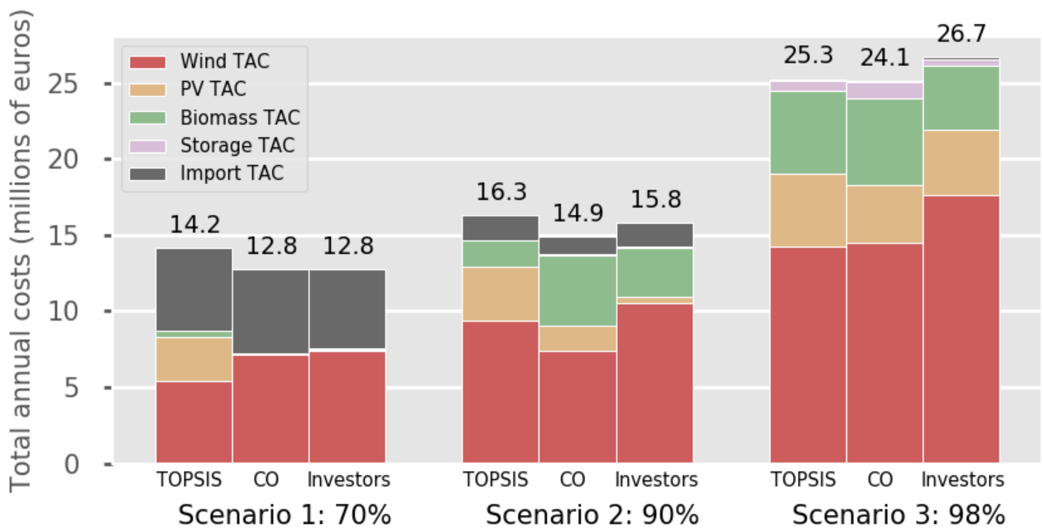

Figure 7.20: Comparing the total annual costs in the total average optimal results (TOPSIS) to the cost optimal solution (CO) and the solution considered optimal by investors. All three scenario's are shown here.

Table 7.3: Comparing the performance of the cost optimal solution and the solution optimal to investors to the average optimal result. The percentages indicate the difference with the average optimal solution. A negative difference indicates that the performance on a specific criterion is better than the average optimal solution.

		LCOE	CapEx	Land use	VIA	**Preference score**
TAC	Scenario 1: 70%	-12%	-13%	+1%	+31%	-21%
	Scenario 2: 90%	+10%	-11%	+34%	-21%	-15%
	Scenario 3: 98%	+2%	0%	+1%	+1%	-3%
Investors	Scenario 1: 70%	-13%	-10%	+5%	+37%	-30%
	Scenario 2: 90%	-4%	-4%	+25%	+12%	-10%
	Scenario 3: 98%	-10%	+7%	+11%	+24%	-7%

Comparing the result found in this chapter to the optimal outcomes for the investors also presents some interesting findings. For all scenarios, investors prefer installing wind turbines over solar, biomass, and storage. Investors are less concerned with land use and visual impact: they are mostly motivated by profits. These results indicate that if the market is left alone, it may converge to a higher share of wind power than is desirable in a future generation mix. This may cause several issues. The land use and visual impact caused by the energy system will be higher than necessary. Also, a big dependence on wind power without flexible generation or energy storage will lead to big problems if there is not enough wind: being only dependent on wind power is a significant risk.

From this section, it can be concluded that including multiple objectives and finding a solution that is agreeable to all actors results in a generation mix that is well-balanced regarding all objectives. Optimizing for cost only or following investors' preferences leads to solutions that have low costs, but do not consider land use or visual impact. This concludes the presentation of the results. The results will be validated and tested in the next chapter.

8

Validation and testing

In the previous chapter, the results of the optimization are presented. This chapter will validate the outcomes of the model with real-world data and compare them to earlier research. After validating the outcomes, section 8.2 discusses the validity of the case-study. Finally, section 8.3 will discuss the sensitivity of the results to a change in input values. An analysis of the robustness of the results to uncertainties is provided in the appendix.

8.1. Validation of the outcomes: is the model an accurate representation of the real world

In section 6.4, the model was verified to represent the conceptual model correctly. In this step, the validity of the results will be evaluated by comparing the results to the real-world situation and other research. First, the four outcomes of the model are compared to real-world data. The four final outcomes are summarized in table 7.2. Also, the cost-optimal generation mix is compared to other literature.

8.1.1. LCOE

The Levelized Cost Of Energy of the system is between 0.03 €/kWh and 0.055 €/kWh. For the optimal average results for all actors, the LCOE is around 0.04 €/kWh. Because this value is thought to represent the price of electricity, the LCOE is compared to average energy prices. TenneT (2018) evaluated the Dutch energy price for 2016, 2017 and 2018 and found that the day-ahead prices rose from an average of 0.039 €/kWh in 2016 to an average of 0.052 €/kWh in 2018. This shows that the LCOE found in the model is in the correct range for electricity prices. In the model, however, much higher shares of renewable energy are found than in real-life. The LCOE for individual technologies is compared to real-life for a better comparison.

The results are shown in table 8.1. The LCOE values for different technologies in this study are comparable to the values found in reports describing the real-life situation.

The LCOE for wind power for this study is 39 €/MWh, which is perfectly in line with real-world data. The LCOE for wind is the average between the LCOE of large wind turbines (28 €/MWh) and for small wind turbines (50 €/MWh). The LCOE of large wind turbines is very low compared to the reports and the value for small wind turbines seems quite high compared to the reports. No reports, however, were found that split up the LCOE for wind power between different sizes of wind turbines. The report from IRENA (2018) calculates the LCOE of wind turbines as an average of several analyzed real-life projects. Many projects that have an LCOE that is even lower than 28 €/MWh have also been found (IRENA, 2018, p.12). It can be concluded that the values found in this research are a reasonable representation of real LCOE values.

Utility-scale solar energy has an LCOE that is within the range specified in the reports. It is on the high side of the range because PV outputs in The Netherlands are mostly lower

Table 8.1: The LCOE (€/MWh) of different technologies in this research compared to several real-life LCOE values for different technologies.

	This study	Lazard (2018)	EIA (2019)	IRENA (2018)
wind	39	35	36	56
PV utility	63	46	37	85
PV res	75	100	-	-
Biomass	-	-	92	62

than in most parts of the world. To confirm this hypothesis, weather data for Madrid was obtained with an average capacity factor of 19%. The resulting LCOE for solar panels in Madrid 48€/MWh. It is concluded that the LCOE of solar panels found in this research is within a realistic range.

The LCOE of biomass energy in the model is not presented in the table. This is because the LCOE of biomass depends on the utilization rate of the biomass plant: if it is used more, LCOE is lower because the investment costs are spread out more. When utilized 100% of the time, the LCOE is around 44 €/MWh. At 35% utilization, the LCOE is around 91€/MWh. This is a good fit with the real world LCOE of biomass represented in table 8.1.

Total LCOE from the model is a simplified and idealized version of reality. Transmission and network costs are not included in the model. Also, the model considers a situation with full knowledge of weather predictions and expected output. In reality, however, this perfect knowledge is not available. Crucially, high shares of RES-E may also lead to more fluctuation in energy prices and high energy prices in times of no wind or solar irradiation. When renewable penetration increases, conventional generation will have to be more flexible: reacting more often and more quickly to changing power supply and demand. This may increase the cost of generation. Also, a higher amount of flexible capacity (which is idle most of the time) may be required to ensure sufficient capacity at all times, even when there is no sun or wind. This has not been taken into account in this research and may lead to higher costs for flexible generation and may increase the overall price of electricity (Hirth et al., 2015).

8.1.2. CapEx and land use

The values for CapEx and land use are directly dependent on the installed capacities. The data-input for these values has been validated with multiple sources in section 6.3. The sources for CapEx and land use were reports analyzing average CapEx and land use for real-world projects. Therefore, it is concluded that the values for land use and CapEx sufficiently represent reality.

It is important to note that limited sources are available for determining land use for biomass feedstock. Although many studies highlight the challenge of large amounts of land use by biomass (e.g., Ignaciuk et al. (2006), Arnette & Zobel (2012) and Harvey & Pilgrim (2011)), only one reliable source was found that provided a number for the amount of land use from biomass (Fthenakis & Chul, 2009). The reason for this is the heterogeneity of biomass feedstock: there is not just one type of biomass. In this research, all biomass energy is assumed to come from cropland. Under this assumption, the results are considered valid. In reality, biomass may also come from waste streams or other sources, however.

8.1.3. VIA

The values found for VIA are not validated here, because no studies have tried to quantify this value. In this research, VIA is represented as an absolute number, but the exact value is not as important. Instead, it is included as a measure to compare different outcomes based on their visual impact: if there are protest groups that are active in the area that object to the placement of wind turbines, which concessions on other areas (regarding cost and land use) will have to be made? The way in which VIA is included in this research is successful in answering this question. Trade-offs between the LCOE and VIA show that large concessions regarding LCOE need to be made to reduce the visual impact by half.

One real-world interpretation of the VIA can be to calculate the number of wind turbines

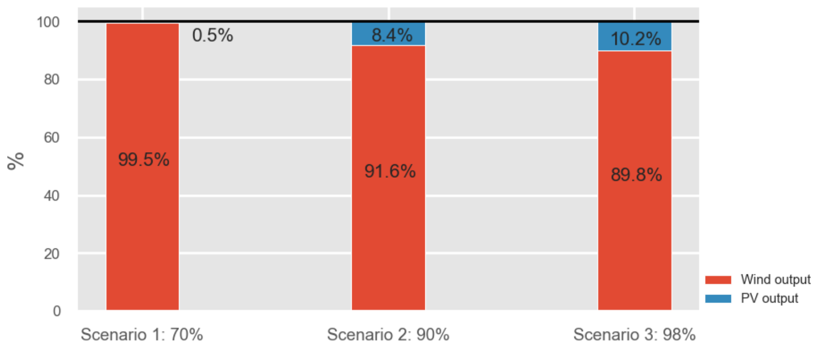

Figure 8.1: The cost-optimal ratio between the output of solar and the output of wind for the three specified scenarios.

visible from anywhere in Goeree by dividing the VIA by the total surface area in Goeree. For the optimal result for 98% emission reduction, the VIA was around 1600 square kilometers. This would mean that, on average, around six wind turbines are visible from anywhere on the island if they were placed in wind farms of 10 wind turbines each.

Although the direct usefulness of VIA is limited, this research presents the first step in including the visual impact of wind turbines in an optimization study. It intends to open the door for more representative, possibly geographically oriented, optimization models to further investigate the visual impact of wind turbines in combination with other important criteria such as cost and land use.

8.1.4. Wind/solar mix in the cost-optimal design

In this section, the cost-optimal generation mix is evaluated to validate whether or not the cost-optimal result is consistent with earlier research. This research has employed a relatively unique (regional) perspective. The only generation methods available within the region are wind, solar, and biomass. Also, this research uniquely uses land use and visual impact as separate criteria. Due to the unique perspective, the results cannot be directly compared to other studies. Several studies, however, have investigated the cost-optimal generation mix at different levels of renewable penetration. The cost-optimal (TAC-optimal) wind/solar mix found in this study are shown in figure 8.1 (as was already shown in figure 7.20).

The cost-optimal mix between wind and solar that is found in this research is under 1% for 70% emission reduction and up to 10% for an almost fully renewable scenario. This result is compared to three studies looking at a European energy system.

De Pater (2016) found a similar result of around 10% solar at 90%, which stayed at 10% when the RES-E penetration was increased to 100%. Becker et al. (2014) found the optimal share of solar to be around 18% solar at 100% renewable penetration. A similar result was found by Rodriguez et al. (2015), who indicated that the optimal mix was around 15% solar at 100% renewable penetration.

At 70% emission reduction, almost no solar is included in the cost-optimal generation mix from this research. From a further examination of the behavior of the cost-optimal system at 70% emission reduction, it is found that the intermittency effects do not really come into play for Goeree: only 5% of the generated electricity is not used in the region and exported. This is shown in figure 8.2, which shows a typical period of three weeks with a cost-optimal generation mix at 70% emission reduction. At 70% emission reduction, it is cheaper to have a small overcapacity in wind turbines than to level out the generation profile by including solar, biomass, or storage. From this, it seems reasonable that having almost only wind energy is indeed the cheapest option.

The cost-optimal mix between solar and wind depends on the capacity factors for both wind and solar in the considered region. Goeree-Overflakkee is a very windy island in The Netherlands. Solar irradiation is lower in The Netherlands than in southern Europe, explaining some of the differences to a European system.

Although Becker et al. (2014) and Rodriguez et al. (2015) find a somewhat higher optimal

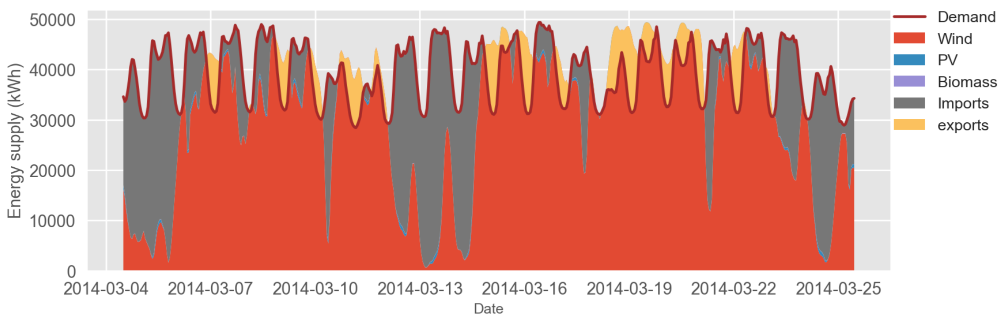

Figure 8.2: Hourly energy production in a typical period of three weeks for the cost optimal system at 70% emission reduction.

share of solar energy in the generation mix, it is still concluded that the values found to be cost-optimal in this research are representative for Goeree-Overflakkee.

8.1.5. Validation of the optimal result for investors

This research found that investors will be mainly drawn towards wind energy. Real-world data for installed capacities in The Netherlands does not directly confirm this result. Table 8.2 shows the total installed capacities for wind, rooftop solar, and utility-scale solar in The Netherlands in 2018. There is an equal amount of wind and solar capacity currently installed in The Netherlands. This research evaluates the wind/solar mix based on the investment costs. Evaluating the installed capacity based on the total investment (using the CapEx for the technologies determined in table 6.2) shows that there is indeed more investment in wind turbines. Based on this research, however, the difference between investments and solar is expected to be bigger than it is in reality.

There is an explanation for the discrepancy between the results of this research and the real-life data, however. This research assumes a central investor that can shape the energy system as they want it. In reality, however, most solar projects are the result of investments of small home-owners (prosumers) putting panels on their roof or companies that install either roof-mounted or ground-mounted solar. These small investors are not able to invest in an enormous project such as a wind farm. This research has approached the energy system from the perspective of a central investor and has not taken the prosumers into account, which will only want to invest in roof-mounted solar panels.

Year reports of big energy companies show that big investors are indeed more drawn towards wind power. Eneco reported 1100MW of installed wind power in The Netherlands, against only 170MW of solar (N.V. Eneco, 2018, p.31). E.ON is a lot more wind oriented and installed 4,555MW of wind energy worldwide versus only 19MW solar (E.ON, 2017). The portfolio of Vattenfall is also wind-oriented. They report that 20.4% of their portfolio is wind power, and only 0.9% is solar power (Vattenfall N.V., 2018, p.8). As can be seen from table 8.2, evaluating the wind/solar mix based on the relative investment shows that the results found in this research are a valid prediction of investor behavior: investors are mainly drawn to investing in wind turbines.

Table 8.2: The installed capacity in The Netherlands in 2018 for solar/wind and the wind/solar mix in the investment portfolio of big energy companies. Source: (CBS, 2019c,d; N.V. Eneco, 2018; E.ON, 2017; Vattenfall N.V., 2018)

Installed capacity in NL	Wind	Rooftop solar	Ground mounted solar
Installed capacity (MW)	4400	4000	400
Investment (Millions of €)	7040	5000	340
Percentage of the total investment	57%	40%	3%

Investment portfolio of big energy producers	Wind	Solar
Eneco	92.4%	7.6%
E.ON	99.7%	0.3%
Vattenfall	97.7%	2.3%

Figure 8.3: Output of solar panels in The Netherlands. Goeree-Overflakkee has been highlighted in red. Reprinted from (Solargis, 2016).

8.2. Validation of the case-study and comparing it to an urban region

This research uses Goeree-Overflakkee as a case study. Goeree is taken to be a representative rural region for the Netherlands. This section reflects on the effect of selecting a different region: how specific to Goeree are the model results? Three properties characterize a region in the model created for this research: the energy demand in the region, the capacity factors for wind and solar in the region, and the available land and roof surface in the region. The expected impacts of these three parameters on the results will now be discussed.

The size of the demand is not expected to change the ratios within the generation mix since CapEx, Land Use, and VIA increase linearly with energy demand. The LCOE will not change if demand is increased. Because the relative change in the different criteria is equal, the generation mix will not be significantly influenced by a differently sized demand only.

The capacity factors in the region do play a big role in the optimal composition of the generation mix. The capacity factors for wind and solar are quite high in Goeree, compared to other regions in The Netherlands. Windspeeds in Goeree are high because Goeree is an island by the sea. Average wind speeds in The Netherlands vary from 5.5 m/s to 8 m/s. Goeree has a relatively high average wind speed of 7.5 m/s (Global Wind Atlas, 2019). Goeree does not only get high wind speeds; it is also a relatively good region for solar energy. This is also shown in figure 8.3. The output of solar panels in Goeree is 15% higher than in some other regions in The Netherlands. If the ratio between the capacity factors for wind and solar is different in another region, the optimal wind/solar mix in the final result is directly influenced and will also be different. The differences within The Netherlands, however, are expected to be relatively small. If, for instance, a region in southern Spain is analyzed, the results may be significantly different. Solar panels will have a much higher output compared to wind turbines.

The available land in the region will also have a significant effect on the generation mix. From the results, it is clear that the constraint on the available land does not influence the optimization results for Goeree: the biggest land use in the outcomes for the third scenario is 70 square kilometers, where 130 square kilometers is available. The reason for this is that Goeree is not densely populated at all (189 citizens/km^2) compared to the Dutch average (411

Table 8.3: Data on the evaluated region regarding population and surface area (sources in text).

	Population	Surface area			Roof surface	
		Total (km^2)	Agriculture (km^2)	Cropland (km^2)	Available (km^2)	Suitable (75%) (km^2)
Goeree	49.500	262	130	105	3.4	2.55
Amsterdam	863.202	165.5	15.9	0.6	14.6	10.95

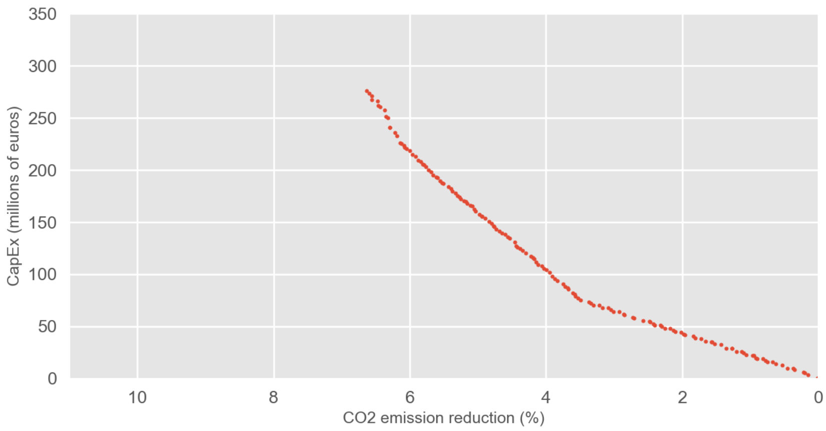

Figure 8.4: Results of the optimization for CapEx and CO_2 for Amsterdam: only 7% CO_2 emissions reduction is possible .

citizens/km^2). Selecting a region that is more densely populated (higher demand per square kilometer) and has a lower capacity factor, will lead to a higher required installed capacity. The required land as a percentage of the total land may be much higher. The next section evaluates the results of the model applied to the municipality of Amsterdam.

8.2.1. Evaluating the possibilities for a regional energy system in Amsterdam

An optimization is performed for Amsterdam using the model created in this research. Two objectives are selected: minimizing CO_2 emissions and minimizing CapEx. The goal here is not to find the optimal generation mix: LCOE, land use and VIA are not included as objectives. The goal is only to investigate which levels of CO_2 reduction are possible at which cost. Amsterdam is very densely populated, and the limited amount of available land for energy generation will influence the results.

Data for Amsterdam is collected from the sources specified in chapter 6. The demand data is calculated by multiplying the total population of Amsterdam (863.202) by the average demand per person in The Netherlands. Amsterdam has an available roof surface of 14.6 km^2 (Broersen, 2018). The agricultural surface area in Amsterdam is only 15.9 km^2 of which only 0.6 km^2 is cropland available for biomass production. The data is compared to the data for Goeree in table 8.3.

Data on capacity factors for solar panels and wind turbines for Amsterdam is taken from the same source as the data for Goeree (www.renewables.ninja (2019)). The capacity factors for Amsterdam are 23% (V66 turbine) and 50% (V112 turbine) for wind (compared to 32% and 58% respectively for Goeree) and 12.9% for solar (compared to 14.6% for Goeree). The capacity factors in Amsterdam are lower than in Goeree.

The result of the optimization (for CO_2 emissions and CapEx) is shown in figure 8.4.

From this figure, it is clear that Amsterdam is not able to reduce the emissions any more than 7%. To reduce emissions by 7%, an investment of 280 million euros would be necessary. Finding land for RES-E is a significant challenge in Amsterdam: even if all rooftops are filled with solar panels, only 7% of the emissions from electricity consumption can be avoided.

Further investigation showed that reducing the emissions by up to 7% will lead to high energy costs in Amsterdam (of 0.054 €/kWh). The reason is that no land is available for cheaper means of electricity production (such as wind turbines and utility-scale solar).

From this section, it can be concluded that each region will face its own challenges. Although the analysis is valid for Goeree, the results are not directly transferable to other regions. When considering another rural region, where land is available, the difference in results will be minor. When evaluating a more urban region, the results are significantly different, and land use becomes an even more pressing issue.

One more observation is that the relative importance of the different criteria may vary significantly for each region. Region strapped for available land will prioritize land use. Regions where a lot of resistance against wind turbines is present will prioritize VIA. Also, some actor groups (investors, governments, consumers, local residents) may be more or less critical depending on the considered region. In this research, all actor groups are considered to be of equal importance.

8.3. Sensitivity analysis

The results from any model depend on the input parameters provided. For the economic and technological parameters, however, no single value is widely accepted to be true, and different reports give different values for cost and land use of different technologies. This section provides a sensitivity analysis to test the influence of a change in parameters on the final results. First, the sensitivity of the results to the input parameters is investigated. Section 8.3.2 analyzes the effect of a changing RRR on the total average optimal result, and section 8.3.3 will determine the effect of changing the weights that are chosen in the processing of the results with the TOPSIS method. The sensitivity analysis in this section will only concern the second scenario that was introduced in the previous chapter. The results for this scenario are assumed to be representative of the other scenarios.

8.3.1. Analyzing the sensitivity to input parameters

The optimization resulted in a set of Pareto-optimal solutions. Changing the input parameters will change the complete set of solutions. Visualizing the difference between two large multi-dimensional data-sets in a simple and easy to interpret manner, however, is not directly possible. Therefore, this section will only analyze the effect of changing some of the input parameters on the total average result.

The most important parameters to consider are the investment costs for the different technologies and land use per technology. VOM of biomass is also included in the sensitivity study. The values for CapEx of each technology, land use, and biomass VOM costs are varied by -20% and +20% to test the effect on the average optimal results. The results are compared to the reference (REF) situation.

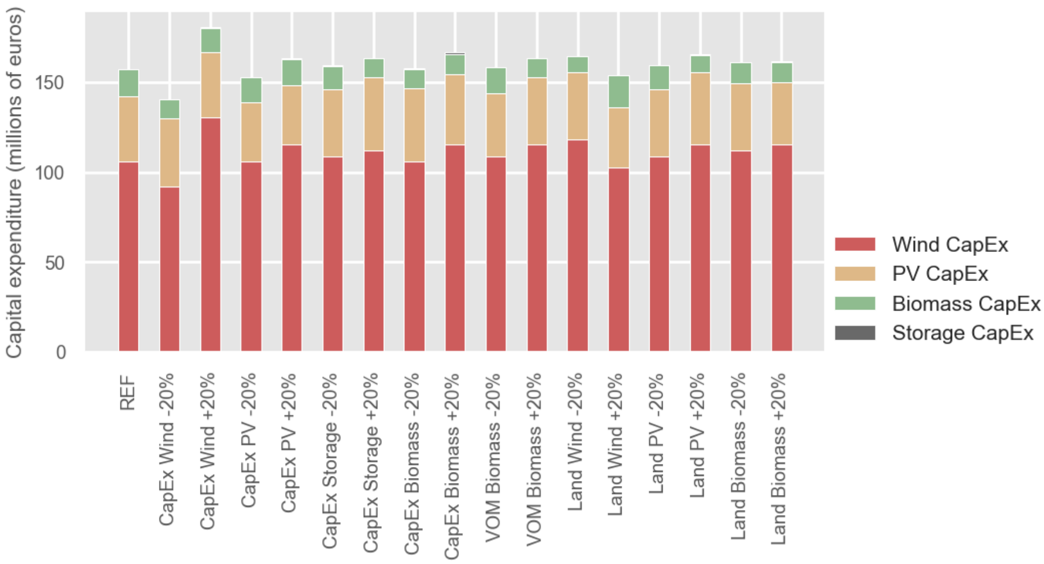

Figure 8.5: Testing the sensitivity of the result to a change in inputs: analyzing the composition of the investment into the energy system.

Figure 8.5 shows the composition of the generation mix in the total average optimal result with different variations in input data. It shows that the costs of wind power have the biggest influence on the total CapEx. This can be expected because wind power makes up most of the generation mix. When biomass is more expensive, or the land requirements for land use are higher, some biomass is replaced with storage in the generation mix, which is interesting.

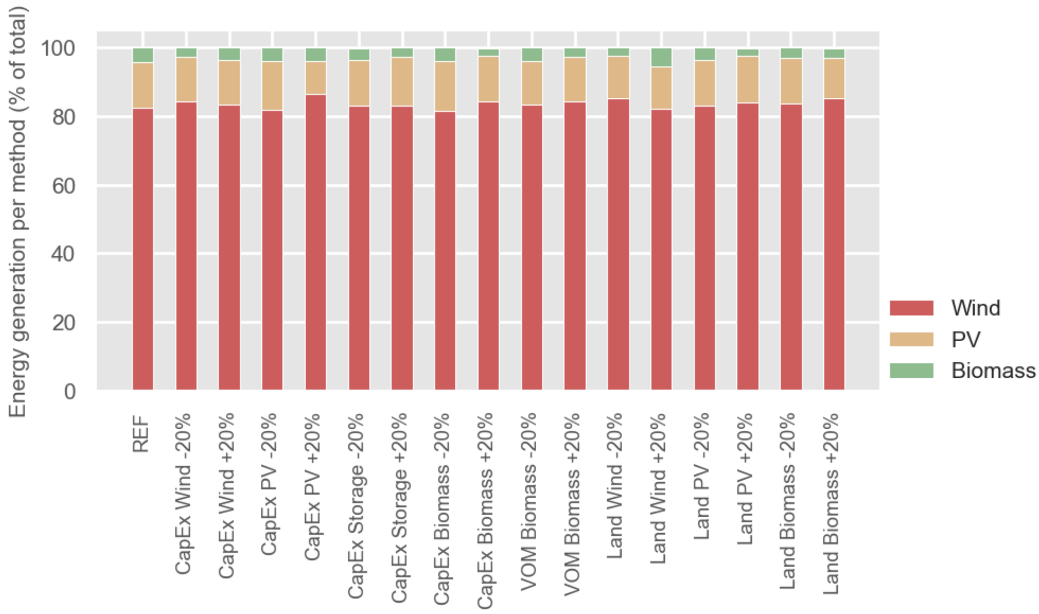

Figure 8.6: Testing the sensitivity of the result to a change in inputs: analyzing the composition of the generation mix by looking at the generated electricity per method.

Figure 8.6 represents the amount of electricity that is generated per method as a percentage of the total generation. It is clear that, although a variation of 20% in costs for a specific technology is quite a significant variation, the composition of the generation mix only varies relatively little in each situation. This indicates that the results are reliable, even if the values for CapEx or VOM change slightly in the future. Interestingly, the cost of PV has a significant effect on the generation mix. Much less PV is included if costs are 20% higher. Having investigated the effects of changing the input data on the final results, the sensitivity to changing the RRR will be analyzed.

8.3.2. Analyzing the sensitivity to a change in RRR

One of the constraints that were defined in section 5.2.2 is that every solution needs to have an IRR that is at least as high as the Required Rate of Return (RRR). The RRR in the optimization was set to a value of 3% based on literature. Different companies in different regions will have a different RRR, however. This value depends on the WACC for the specific investor. In this section, the sensitivity of the total average optimal result to a change in RRR is analyzed. Six scenarios are analyzed with the RRR ranging from 0% to 5%. Again, only the second scenario (90% emission reduction) is analyzed. The results are shown in figure 8.7.

From this figure, it can be seen that the share of wind turbines in the total average optimal generation mix increases with an increasing RRR. The share of solar and biomass decreases, which is interesting and can be attributed to the following effect: the constraint on IRR puts an upper limit on the LCOE that a solution can have (because LCOE and IRR are correlated). By reducing the RRR, the upper limit on LCOE will be higher: more expensive solutions are included. This skews the total set of solutions more towards expensive solutions. The total average optimal solution is determined based on the relative desirability compared to the total set. If more expensive solutions are included, the total average optimal result will also be a bit more expensive (include fewer wind turbines). If less expensive solutions are included, the total average result will also be slightly less expensive, and more wind turbines

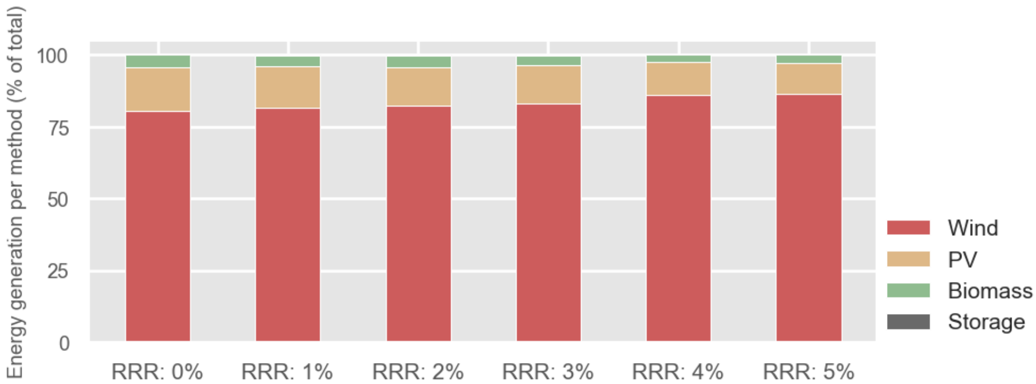

Figure 8.7: Testing the sensitivity of the result to a change in RRR: analyzing the composition of the generation mix by looking at the generated electricity per method. The reference scenario (RRR of 3%) is also shown.

Table 8.4: Different weights allocated to the actors in each of the investigated scenarios. REF is the reference scenario that was presented in the previous chapter. AM is the result with taking the arithmetic mean instead of the geometric mean.

Scenario name	Government	Investors	Local residents	Consumers	
REF	1	1	1	1	*Geometric mean*
AM	1	1	1	1	*Arithmetic mean*
Govt 2x	2	1	1	1	*Arithmetic mean*
Inv 2x	1	2	1	1	*Arithmetic mean*
Res 2x	1	1	2	1	*Arithmetic mean*
Cons 2x	1	1	1	2	*Arithmetic mean*

are included. The results are somewhat sensitive to a change in RRR, and more analysis is required to find a regionally specific RRR. The next section will analyze the sensitivity to changing the weights used to determine the total average optimal results.

8.3.3. Analyzing the sensitivity of the weights applied in the MCDM

In the previous chapter, the Pareto-front was analyzed with a MCDM method (TOPSIS). This resulted in a final total average result that most desirable for all actors. The weighing of the different criteria and the different actors will have a significant effect on the results. As was indicated, this research assumes equal weights for all criteria and also equal weights for all actors. This simplification is necessary to be able to process the results with the limited information available and show that the method proposed is promising. This section will investigate the effect of changing the weights used in MCDM to obtain the final result.

The average optimal result has been calculated again from the Pareto-front with different weights allocated to the actor groups. Five scenarios for weighing the actor groups are evaluated, which are introduced in table 8.4. In the previous chapter, the geometric average was taken, as proposed by Shih et al. (2007). To be able to allocate weights to the different actors, one cannot use the geometric mean (because it multiplies all elements individually). The arithmetic mean is therefore used to weigh the different actors in this section. The results are shown in figure 8.8.

As can be seen in figure 8.8, taking the arithmetic mean instead of the geometric mean already changes the results. The arithmetic mean is less sensitive to one single low value and therefore returns an average that is more attractive to investors with more wind turbines and less PV; the low satisfaction of residents is not taken into account as much. If the government is allocated a higher weight, the results are the same as the geometric average. When residents are allocated a higher weight, more biomass is included to minimize the required amount of wind turbines.

The results in this section show that the average optimal result is quite strongly dependent on the way the different actor groups are weighed. Only changing the weight of one actor from one to two will already change the results, and bigger variations in weights are expected to lead to even bigger differences. The preferences of the actors are quite far apart and allocating one actor group with a higher weight results in a different average preference. In this section,

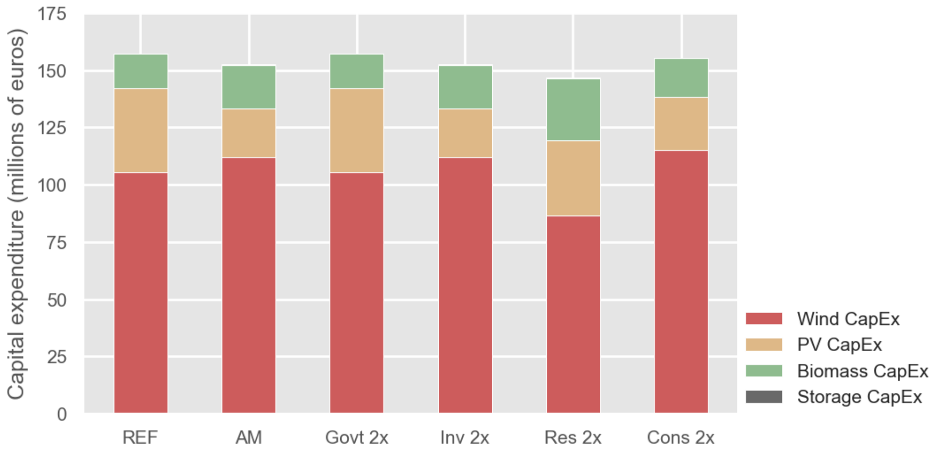

Figure 8.8: Sensitivity of the final average optimal result for the second scenario to changing the weights allocated to the different actor groups. Scenarios introduced in table 8.4.

only the effect of weighing the actor groups in different ways is investigated. Governments and investors regard multiple criteria to be important. In this research, each criterion has an equal share in the preference of governments and investors. Changing the priority of governments and investors for different criteria will also influence their preferred solution.

8.4. Conclusions from this chapter

In this chapter, the results are validated to be a correct representation of the real-world. It is shown that the values found for LCOE are representative and that the cost-optimal wind/solar mix corresponds to earlier research. It is also found that, in accordance with the results, investors are significantly more inclined to invest in wind power than in solar power.

The validity of the case-study (Goeree) is also discussed. The results are argued to be representative of a rural region where enough land is available. The optimal generation mix found for Goeree will be similar in another rural region in The Netherlands. Running the model for the municipality of Amsterdam showed that the results will be significantly different for an urban environment, because much less land is available. Three different sensitivity studies are completed, from which interesting conclusions can be drawn.

Differences in input values for land use and investment cost for different technologies do influence the composition of the optimal generation mix, as can be expected. If prices change, the results will be different, and up-to-date prices should always be used. Changing the Required Rate of Return also influences the total average optimal result. By changing the value for RRR, the boundaries of the Pareto-front are altered, leading to slightly different total average optimal results. The effect of changing the weights used in MCDM, however, is considerably more significant. The final average result depends on the way that weights are allocated. From this, it is clear that if the model were used to deliver actual policy advice, much attention should go to the way that the results are processed. More research and interaction with the involved actors is necessary to be able to formulate a more representative optimal result. The analysis is still relevant for two main reasons. Firstly, performing MCDM from the perspective of multiple actors has been shown to be a viable method to find the average optimal result from a large Pareto-front. Although the final result may not be fully representative, it was able to identify an, on average, acceptable result for all actors. Secondly, generating a large Pareto-front and processing it with MCDM has led to increased insight into the behavior of the system and into possible optimal solutions for different stakeholders. The trade-offs to be made between the preferences of the different actors have become apparent, and this may be very valuable to planners of a regional energy system.

This concludes this chapter. Appendix F provides one additional analysis: the robustness analysis of the total average optimal result. In reality, many uncertainties influence the design. The robustness analysis evaluates the robustness of the results to these uncertainties. The next chapter will discuss the results and some limitations.

9
Discussion

Chapter 7 has presented the results of the study and the results were validated in chapter 8. In this chapter, the implications of the results to power system planners are discussed. Finally, section 9.2 will elaborate on some relevant limitations of this research.

The results show that multi-objective optimization can successfully be used in combination with MCDM from a multi-actor perspective to find an optimal generation mix for a specific region, taking into account land use and VIA. This study extends the field of power systems optimizations in two main ways: firstly, it was seen that when land use and VIA are taken into account, a design can be found that performs significantly better than a least-cost solution regarding land use, VIA and stakeholder preferences (table 7.3). This design may be better suited for real-world implementation. Secondly, it is shown that by performing a multi-objective optimization, the optimal results for different actors can be compared, leading to more insight into possible designs of the system. The model created is generic for any region. It is most valid, however, for relatively small regions because only one node is included: all energy demand and supply takes place in one location. Also, it requires the assumption that flexibility can at all times be guaranteed through a grid connection, making it less suitable for analyzing a national energy system. From this study, several interesting implications for power systems planners can be identified, which will be discussed now.

9.1. Discussions of the result and implications to power system planners

Section 1.2.2 introduced the issues of spatial integration and local acceptance. In the transformation of the energy system, these are key issues and only focusing on the technological side of the energy system will lead to a design that may not be fully suited for real-world implementation. Especially since urban areas in The Netherlands have the highest ambitions regarding the energy transition (BMC, 2018) and will struggle even more with spatial integration and local acceptance. Approaching the challenge from a regional perspective will make it easier to guarantee local acceptance and proper spatial integration and taking these elements into account in the design is very important. It is found that by minimizing land use and the visual impact of wind turbines, a design can be found that is more desirable for all stakeholders. The resulting design for Goeree includes more solar energy than a least-cost solution and the solution optimal to investors. No residential solar or small wind turbines are included in the optimal generation mix: the reduction in land use and visual impact is not enough to weigh up to the higher costs. The results are discussed below. For clarity, the section is split up into five subjects of discussion.

9.1.1. Energy costs, land use and visual impact in a future energy system

Completely eliminating emissions from electricity generation is theoretically possible in Goeree-Overflakkee (figure 6.10). A relatively small investment of 2000 euros per citizen would be required to reduce emissions by 70%. Further reductions in emissions require many investments. To reduce emissions by 98% in the future and generate almost all energy within the region, around 5500 euros per citizen is required in Goeree. This still seems an attainable goal for the future. Land requirements for energy generation will be high in the future. When reducing the emissions in Goeree by 90%, a quarter of the available land in Goeree needs to be used for energy generation, and when 98% reduction is the target, a third of the land will be required. Goeree is not densely populated, and there is plenty of available land: the challenge will be even bigger in a more populated area. By applying the model to the municipality of Amsterdam, it is shown that Amsterdam is not able to independently reduce emissions from the electricity system by over 7% because of the limited availability of land. Cooperation between different regions will be necessary to reach the national goals.

The visual impact of wind turbines will also be significant in a future energy system, even if it is taken into account in the design. If 98% of emissions are to be avoided, up to six wind turbines are visible from anywhere on the island. This is a significant impact and underpins even more why this should be taken into consideration. Integrating renewable energy into the energy system, however, will not increase the energy price since wind and solar energy are already competitive with conventional generation.

9.1.2. Flexibility requirements in a future energy system

The national targets of 70% emission reduction can be achieved in Goeree without requiring additional flexible generation or energy storage to be installed in the region. A combination of wind and solar is sufficient. The cheapest option would even be to have only wind turbines in the generation mix, but including solar is more desirable. The technologies already exist, and the national target for 2030 seems achievable. After this target has been achieved, and even more RES-E are integrated into the energy system, significant investments in biomass energy or energy storage are required to balance demand and supply. Decision-makers need to prepare for increasing the amount of sustainable flexible capacity well ahead of time to ensure that flexibility can be guaranteed at all times.

9.1.3. Differences in stakeholder preferences regarding an optimal design

There is a strong difference in preference for the design of the energy system between different stakeholders. In the liberalized energy market, investors have a considerable influence on the final design of the energy system. The investors will want a design that includes more wind turbines. This was also seen in real-world data (section 8.1.5). If the market is left alone, an energy system with undesirable consequences for other stakeholders may be the result. Table 7.3 showed that land use and VIA may be up to 40% higher if investors get a full say in designing the energy system. Local residents can be very vocal in preventing the placement of wind turbines, and the interests of this group should be taken into account when designing an energy system. Governments favor a more balanced generation mix and may want to implement policies that benefit solar energy to reduce land use and visual impact. It is also found that, although including more energy storage in the generation mix will significantly reduce the required land when emissions are reduced by 90% or 98%, storage plays a minimal role in the most desirable generation mix: it is still too expensive. From figure 8.5, it is clear that even when costs for storage are reduced by 20%, storage is still only a small part of the most desirable generation mix. Governments may want to focus on bringing increased attention to the development of efficient energy storage and implement policies that stimulate investors to invest in energy storage in the future.

9.1.4. Future dependence on wind energy: a possible risk

This research suggests that a strong dependence on wind energy in the future is necessary, even when land use and the visual impact of wind turbines are taken into account. This dependence on wind energy may be a risk to the security of supply. In the future, wind energy may provide 70% of all energy nation-wide. If there is little wind for an extended time, a large amount of flexible generation capacity or energy storage is necessary to guarantee the security of supply. Power system planners should take this consideration into account to guarantee a stable power supply. The high amount of wind turbines required for energy generation will also result in high amounts of land use and visual impact. Power system planners should ensure the inclusion of all actors in the decision-making process to make sure that all interests are taken into account.

9.1.5. Comparing the results to a cost-optimal design
In the past, researchers mostly investigated the optimal design of an energy system regarding costs. Other researchers performed multi-objective optimizations considering technological objectives (reliability, wasted renewable energy). The immense challenges of spatial integration and local acceptance had not yet been included in energy systems optimizations. The results from the optimization are compared with a least-cost solution in section 7.6. It is shown that including land use and visual impact greatly improves the design in this area, especially for the 70% and 90% emission reduction scenarios.

Interestingly, for the scenario reducing emissions by 98%, the least-cost solution performs comparably to the most desirable solution, although the total average optimal result still performs slightly better (see figure 7.20 and table 7.3). Some proximity of the least-cost result to the most desirable result can be expected since cost is an important consideration for all actors. The close similarity of the two solutions, however, is still interesting. The least-cost solution tries to minimize the required resources. Apparently, for the third scenario, the solution that has the least cost also performs relatively well on land use and visual impact. The costs of reducing land use and visual impact more are too high to be desirable. Although the least-cost solution is a close approximation of the optimal result, considering land use and visual impact is still relevant. If only costs are minimized, there is no insight into other solutions that could have been even more desirable.

The results of this study show that including land use and VIA is possible and can lead to a more desirable design that requires less land and VIA. It can also be argued that performing a multi-objective optimization is a good way of approaching the design of an energy system in a complex socio-technical environment. There are two main reasons for this. Firstly, optimizing for a single objective will present a solution that is extremely well suited (optimal) for the objective that is minimized. As was seen from investigating the trade-offs between the different objectives, an optimal solution for one objective (e.g. CapEx) will have an extremely undesirable result for another objective (e.g. land use), especially when comparing the first and second scenario to the least-cost solution. Secondly, multi-objective optimization is interesting because it shows that there is not just one optimal solution. Many different designs are possible and can be compared to each other on their relative desirability. This way, the most feasible design can be found by engaging with stakeholders. As such, the model can be used to foster learning with decision-makers rather than dictate choice.

Now that some of the main implications of the results to power systems planners have been discussed, the next section will discuss several limitations to this research.

9.2. Limitations of this research
The results presented in chapter 7 where tested and validated in chapter 8. Although the results were found to be a close approximation of what a realistic outcome would look like, the results found and the model used to obtain the results do have some important limitations. As was wisely stated by Box & Draper (1987, p.424): *"Essentially, all models are wrong, but some are useful."* To be able to draw meaningful conclusions based on the model created for this research, this section will reflect on the most important limitations of the model.

9.2.1. Modelling in a complex socio-technical system
The model created in this study assumes a central planner and decision-maker. In reality, investment decisions are not taken by one actor, but many smaller investment decisions are made, which result in a final design: the energy system emerges from the interaction between many different actors. The final design will likely not correspond directly to the optimal design as is also seen from table 8.2. The transition in the energy system is the result of interactions between many different stakeholders and the success depends on a large combination of contextual factors (Sperling, 2017). Knowing what an optimal design may look like, however, will help policymakers to develop policies that steer the market towards a more optimal design for the energy system. Although the model created in this study inevitably simplifies the real-world situation, it aims to function as a basis for discussion. The model can be used to learn more about the functioning of the system. Design of a socio-technical system should be a

process of design and redesign. Iteration between model-based analysis and stakeholder interaction is paramount and will lead to better models and better results (Pfenninger et al., 2014).

9.2.2. Simplifications made in the model

The simulation model that was used in this research has several important simplifications. These will now be discussed based on four categories of limitations. Some limitations regarding the scope of the model are discussed first.

Scope considerations

Firstly, only one node was used in the model (see section 4.2.1). Aggregating all demand to one node means that there is no information on where the ideal placement of RES-E would be in the region. Including multiple nodes will lead to a better design because an optimal distribution of RES-E can be found. Goeree, however, is relatively small, so the differences in the weather in the region will also be small and the resulting generation mix will likely be similar. The aggregation into one node also means that no network and transmission of energy is included. This leads to an underestimation of the required costs, but will probably not change the optimal generation mix found in this research.

Also, only a small selection of technologies is included in this study. No off-shore wind turbines, long term energy storage or hydropower is included. Including any of these may lead to a better design with lower costs, land use, and visual impact. In an ideal scenario, the model would have been simulated over several decades and used a smaller resolution. Due to limitations in computing power and available data, this cannot be done. Bias in the data for the considered year may have altered the results slightly. Also, using an hourly resolution smooths out some of the peaks that can be expected in demand and supply on a smaller time-scale. This likely leads to a slight underestimation of the required capacity and flexibility.

Limitations in defining the optimization objectives

Visual impact and land use are represented in a simplified way. All land use is aggregated to one number to allow for analysis. Land use in reality, however, is more nuanced. Wind turbines are placed in wind farms, but the area can still be used for food production. This is not the case for a utility-scale solar plant. Although aggregating all land use to one number was necessary, the way in which land use is evaluated has significantly affected the results. If a different choice is made in how land use is aggregated, the final results will be different.

The visual impact is measured by the impacted area. Wind turbines are assumed to be placed in wind farms of ten turbines that are evenly spread out across the region for the assessment of their visual impact. The area that is visually impacted will be different if wind turbines are not placed in wind farms of ten turbines or if the area that is visually impacted by two wind farms has an overlap. The size and layout of wind farms are key factors in the visual impact of wind power: small farms in a structured layout are more easily accepted (Devine-wright, 2005). This research has not taken this into account. More research is required into how these simplifications influence the results, and no direct conclusions can be drawn on the area that is visually impacted. Defining an area that is visually impacted, however, has allowed the criterion to be included in the optimization and is a suitable way to minimize the number of wind turbines while taking into account the relative impact of differently sized turbines.

As was discussed in section 5.1.1, a maximum of three objectives can be included in the optimization. The result of this limitation is that CapEx could not be included as a separate objective. If computing power was not limited, a better solution could be found by including CapEx as an objective. As was shown in appendix D, including VIA in favor of CapEx led to higher costs, although the difference was small.

Limits to the regional approach with a grid connection

This study approaches the challenge of designing an energy system purely from a regional perspective, and only RES-E are included in the optimization. It is assumed that flexibility can be guaranteed at all times through a connection to the grid and all surpluses in electricity can be sold back to the grid. If all regions in The Netherlands use this perspective, however, no region will take into account that the total supply needs to be equal to demand and not enough flexibility is introduced into the energy system. This may result in higher prices and enormous price fluctuations. Reasoning according to Kant's categorical imperative *(one should only act a certain way if he wishes this behavior would become a universal law)*, becoming energy neutral without focusing on energy storage and flexible generation is not a good way to act. In the future, the grid may need to be split up into several, completely stand-alone sections where each region guarantees its own flexibility (Østergaard, 2009).

In addition to this, flexible generation will become less efficient if RES-E shares are increased. The amount of time that conventional power plants are dispatched will decrease and power plants also need to be more flexible to adapt to the intermittent energy supply of RES-E. The operational costs of these conventional power plants will rise and these effects may increase the costs of energy significantly in a future energy system (Van Den Bergh & Delarue, 2015; Brouwer et al., 2014).

Uncertainties that may influence the result

Deterministic weather and demand data are used in this research, which means that perfect foresight into the expected generation is assumed: the central planner knows exactly what conditions to expect. In reality, the weather is very unpredictable, and the assumption of perfect foresight likely leads to an underestimation of the required back-up capacity to guarantee flexibility at all times.

Finally, the genetic algorithm used to obtain the results is stochastic in nature: the results will be slightly different after each optimization because different points on the Pareto-front are found. This is not expected to have a great influence on the overall results, but increasing the population size even further will improve the accuracy of the results.

9.2.3. Limitations in processing the results through MCDM

The results from the multi-objective optimization were processed with MCDM. The allocation of weights is the first limitation of this approach. In section 8.3 it was already seen that the final optimal result depends significantly on the weights allocated to the different actors in the MCDM and which actors are included. Not much information is available on how to accurately weigh the different preferences. The only way an accurate estimation of weights could be obtained is through intensive interaction with different stakeholders. This is beyond the scope of this study, and although the model itself is still valid, no decisions should be made solely on the final result of this study. Also, the TSO and DSO were not found to have relevant interests to this research (because of the exclusion of networks and the guarantee of reliability through a grid-connection). In reality, however, they are crucial actors and should not be overseen in decision making. The second limitation of this approach is that the desirability of the results is only evaluated based on a comparison to other results in the Pareto-front. From this, it follows that the total average optimal result depends on the composition of the Pareto-front (and the dimensions of the solution space) and is not universal.

The method used to process the results is not perfect, but it is still a good solution. Another option would be to aggregate the objectives before performing the optimization. This would result in only one solution and would not lead to insight into the functioning of the system and still requires weighing the different objectives. The method proposed in this research is not perfect but processing the results after the optimization (a posteriori) leads to more insight than aggregating the objectives before the optimization (a priori).

Although the model knows several limitations, the results are very relevant and can be used as a basis for discussion between decision-makers. It paints a picture for a possibly ideal energy system in the future. Also, the inclusion of land use and visual impact as separate objectives has led to a design that is more reflective of the preferences of different stakeholders. Performing a multi-objective optimization and analyzing the Pareto-front has shown that many solutions exist and that stakeholder preferences eventually decide which design is most desirable.

10

Conclusion and recommendations

In this chapter, the conclusions and recommendations based on the findings in this research are presented. First, the research questions that have been formulated in the first chapter are answered, followed by recommendations for further research in section 10.3.

10.1. Answering the main research question

The main research question to be answered in this research was defined as:

What is the most desirable generation mix for a regional energy system to meet the energy transition targets for 2030 and beyond, taking multiple objectives into account from a multi-actor perspective?

The answer to this question based on this research can be formulated as: by including land use and visual impact in an energy systems optimization in addition to cost, a design can be found that is significantly more desirable to all involved stakeholders. The most desirable generation mix depends on actor preferences and includes much more solar energy than a cost-optimal generation mix. This section will elaborate on the main findings.

The first step in answering the research question is to define what a desirable generation mix is. In this research, it is argued that a design for a regional energy system should be designed for minimal cost, land use, and visual impact. There is not one single design for a regional energy system that is optimal regarding all objectives: the optimization has resulted in a Pareto-front of non-dominated solutions. Which of the solutions on the Pareto-front is most desirable depends on actor preferences: different actors have different preferences. These conflicting views on the optimal design are typical for a complex socio-technical system: the complexity of the challenge is increased by the different views of the involved actors.

To reflect on possible solutions to this problem, a multi-objective optimization model is created, which is solved using a genetic algorithm (NSGA-II). As a case-study, the region of Goeree-Overflakkee is analyzed. Three different scenarios are investigated: reducing emissions by 70% to reach the national targets, reducing emissions by 90% to surpass the targets and reducing emissions by 98% to become almost fully self-sufficient as a region. For each scenario, a unique Pareto-front is found. The results show that there are many designs possible for a future energy system. When 70% of the emissions need to be avoided, no flexible generation in the region is necessary. Only wind and solar can be sufficient to fulfill demand. If 90% or 98% of the emissions need to be avoided, flexible capacity from biomass energy or energy storage is required to be able to fulfill demand. Costs, land use and visual impact all increase significantly above an emission reduction of 80%: the intermittent supply from RES-E means that a significant amount of flexible capacity, overcapacity or energy storage is required to be able to fulfill demand.

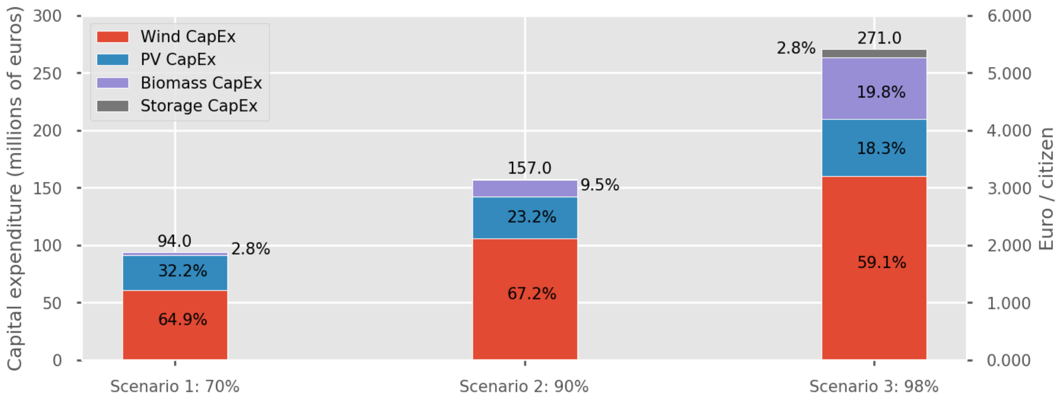

Figure 10.1: Total average optimal results in Goeree for each scenario. The generation mix is represented based on the share of each element in the total investment.

Table 10.1: Final optimal results for Goeree (averaged for all actors) for the four most important criteria.

Scenario:	**LCOE** (€/kWh)	**CapEx** (millions of €)	**Land Use** (km^2)	**VIA** (km^2)
1: 70% reduction	0.041	94	17.1	621
2: 90% reduction	0.037	157	30.8	1080
3: 98% reduction	0.041	271	45.4	1636

Analyzing the three different Pareto-fronts showed that there are significant trade-offs between the objectives. Investors favor a solution with the lowest costs and will prefer a solution with a high amount of wind turbines. Local residents will not be satisfied with this solution, however. Governments are concerned with minimizing land use and favor a design that includes more solar energy. In the scenario of 98% emission reduction, the optimal design for the governments also includes around 10% energy storage to reduce the required land.

In the end, the main research question looks for a single most desirable generation mix. In this research, the average preference of all actors is argued to represent an acceptable solution for all actors. Although there are some limitations in the way that the weights have been applied, taking the average preferred result leads to a design that seems well balanced across all objectives. The total average optimal results for all actors in each of the scenarios has been represented in figure 10.1. This figure clearly shows that a balance between wind and solar is preferred. When 98% of the emissions need to be avoided, 20% of the investment goes towards biomass for flexible generation. It can be seen that a significant increase in investment is needed to reduce emissions from 90% to 98%.

Table 10.1 summarizes the effects that the average optimal result will have on the costs, land use, and visual impact. Increasing the share of RES-E in the generation mix does not increase LCOE. Land use and visual impact, however, increase significantly.

It is argued that the results are valid for a rural region. If applied to an urban region, however, the model shows that there will not be enough land available: in Amsterdam, a maximum of 6% of the emissions can be avoided by generating electricity in the region due to the limited availability of land.

10.2. Answering the sub-questions

The section above provides a complete answer to the main research question. To be able to answer this main research question, several sub-questions also needed to be answered. The answers to the sub-questions are now discussed.

Which stakeholders are involved in the transition to a renewable regional energy system and what are their interests? Many stakeholders play a role in the energy transition. A key part is played by four groups of actors with different interests: governments, investors, consumers, and local residents. The different levels of government all play an important role. The national government formulates targets for the energy transition: they want to guarantee affordability and security of the electricity supply and want to decrease the emissions from electricity generation. The national government has indicated that focusing on a regional scale will make it more feasible to integrate RES-E into society and solve the barriers of spatial integration and social acceptance. Provincial and municipal governments are tasked with allocating land for RES-E projects and engaging with stakeholders to ensure acceptance of the energy system. Another vital role is played by energy producers and energy cooperatives: the investors. Most energy producers are big companies that invest in RES-E and are mainly profit-oriented: they focus on creating value for their stakeholders, but are also increasingly concerned with sustainability. The role of energy cooperatives has also become larger: in the last ten years, energy cooperatives have enabled 70.000 citizens to invest in renewable energy. Consumers are increasingly concerned with the environment and have significant market power: they decide where they buy their electricity. The main interest of the consumers, however, is still to have a low energy bill: they want affordable electricity. Finally, resistance against the placement of RES-E (mainly wind turbines) is playing a big role in the Dutch energy transition. Local residents may not agree with the placement of wind turbines in the region. They must be involved in the decision and can prevent the installation of RES-E in court if they feel that they have not been properly heard. The main concern of local residents is the visual impact of wind turbines: wind turbines are felt to reduce the quality of the landscape. An energy system with fewer wind turbines would be more desirable for local residents.

Which criteria should be considered when attempting to find an optimal generation mix? Most studies investigating the optimal generation mix for a renewable energy system have only designed for minimal overall cost. This research has set out to define the most important criteria in designing an energy system that can actually be implemented. This entails a shift from modeling for a theoretical optimum to modeling for the most desirable design. The four most important criteria are identified: LCOE, investment cost, land use, and the visual impact of wind turbines. Each of these is shortly discussed.

LCOE represents the total average cost incurred in generating one kWh of electricity in the region. It is vital to keep costs low for two reasons: the consumers want to have a cheap supply of electricity and will support cheap technologies. Also, investors will want to keep LCOE to a minimum because generating electricity at a lower price will increase the returns on the investments: lower LCOE is directly correlated with a higher internal rate of return.

CapEx is also minimized. Even though the LCOE for RES-E is competitive with fossil fuel-based alternatives, the up-front investment costs for RES-E are much higher. The high investment costs present a significant barrier to investors. When the investment costs are minimized, the final design will be more feasible, and finding investors will be easier.

Land use for energy generation is one of the main barriers to the energy transition in The Netherlands. The Dutch government has even allocated a separate section in the climate accord to this challenge. Land used for energy generation should also be minimized to find a design that makes spatial integration possible.

The visual impact of wind turbines is also a barrier to the energy transition resulting in a lack of local acceptance. To satisfy local residents and design an energy system with the least amount of wind turbines possible, the area that is visually impacted by wind turbines should also be minimized.

How can an optimization problem be defined taking into account the most important objectives of the actors? In answer to the previous research question, four important objectives to the actors were defined. The optimization should minimize these four objectives. In this research, it is argued that performing a multi-objective optimization leads to more insight into the functioning of the system than aggregating the objectives before doing the optimization. A maximum of three objectives can be included due to limitations in computing power. Therefore, CapEx had to be excluded as a separate objective. The decision variables in the optimization are defined to be the installed capacities of the different technologies. These can be altered to find the optimal design that minimizes the objectives. The decision variables are used as an input in a simulation model. This model simulates a year of energy production and demand in Goeree-Overflakkee and returns the values for the objectives as an output.

The design needs to be able to achieve a certain degree of emission reduction. This is included as a constraint, and three different scenarios of CO_2 reduction are identified. Several other constraints are also taken into account to make sure that a realistic design for the system is achieved. The most important constraints are a minimal value for IRR and a maximal value for land use based on the available land in the region.

In this research, the widely applied genetic multi-objective optimization algorithm called NSGA-II (Non-dominated Sorting Genetic Algorithm II) is used to solve the optimization.

What is the effect of the different elements of the energy system on the different criteria? The optimization described in the previous section results in a Pareto-front of 3000 outcomes. This set of outcomes can be analyzed to see the relation between different generation methods and different objectives. From this analysis, it is clear that wind energy is the cheapest means of generating power. Including more wind power in the generation mix leads to a lower LCOE. In order to minimize CapEx when 90% or 98% of the emissions are reduced, there is an optimum share of wind energy (at around 60%, see figure 7.2). This shows that at higher levels of emission reduction, the effects of intermittency really come into play. Wind turbines have a significant visual impact, and including more wind turbines in the generation mix will increase this impact.

Including more solar energy reduces the required amount of land, but results in higher cost: the LCOE and CapEx are negatively influenced by solar energy. When a high share of renewables is required, however, including some solar (instead of wind) will actually decrease the required investment because the supply and demand profiles are more compatible. Including more solar energy in the generation mix can replace wind energy, lowering the visual impact and land use of wind turbines.

Short-term energy storage is not yet economically attractive: including energy storage will increase the total costs incurred. Both LCOE and CapEx are negatively influenced by increasing the amount of energy storage. Storage, however, can be successfully used to reduce the amount of required land when high shares of renewables are included in the generation mix. In the third scenario, with 98% emission reduction, putting 20% of the total investment into energy storage can reduce the required land by a third.

Energy from biomass plays an interesting role in a regional energy system as a means to guarantee flexibility. Biomass is a cheaper option than energy storage. At 90% or 98% emissions reduction, a significant amount of biomass energy needs to be included to guarantee flexibility. Generating electricity from biomass, however, requires a large transformation of land to produce enough crops for biomass.

Which trade-offs between different criteria can be identified from analyzing the Pareto front? From analyzing the Pareto-fronts, it is clear that there is a significant trade-off between investment cost and land use and investment cost and visual impact: reducing visual impact and land use will come at a cost. Investing 30% more can reduce the required amount of land by almost half. A similar trade-off is found between CapEx and the visual impact of wind turbines.

An important conclusion from analyzing the trade-offs is that minimizing only one single objective will result in a design that is optimally suited for one criterion. Other relevant criteria, however, will have an extremely unfavorable value if the results from a single-objective optimization are implemented. This indicates that including multiple objectives will result in a more balanced design.

What is the most desirable generation mix for different actors in each scenario of CO_2 reduction? The four main actor groups that were identified are governments, investors, consumers, and local residents.

Governments are concerned with minimizing land use, visual impact, and LCOE. Because of this diverse set of interests, governments favor a balanced generation mix. The generation mix should result in an optimal trade-off between the different objectives. A relatively high share of solar is preferred. Also, governments favor some investment in energy storage if emissions are to be reduced by 90% or more.

Investors are mainly concerned with LCOE and CapEx. The results of this study show that LCOE and CapEx are minimized by including a high share of wind turbines in the generation mix. At 70% emissions reduction, investing only in wind turbines is most efficient. At higher shares of RES-E integration, the investors favor a share of around 80% wind turbines. The investors do not want to invest in energy storage because returns on investing in energy storage are too low.

Consumers are price-oriented. In the model created for this research, because of the assumption that all energy can be sold to the main grid at all times, building more wind turbines decreases the LCOE. Therefore, consumers have a strong preference for a generation mix that only includes wind turbines. Local residents, on the other hand, are only assumed to be concerned with minimizing the visual impact of wind turbines. Therefore, they prefer a generation mix with the lowest amount of wind turbines possible.

What is the benefit of including multiple objectives in the optimization other than cost? This research has shown that including multiple objectives in an energy systems optimization is possible, even if the objectives one wants to include are not purely technological in nature. Including multiple objectives in the optimization has two main benefits.

Firstly, including multiple objectives in the optimization ensures that important criteria, in addition to cost, are taken into account. When choosing a generation mix, there is a Pareto-front between costs and land use and costs and visual impact. Minimizing only costs will result in a solution that is on one side of this Pareto-front: it results in high land use and visual impact. If multiple objectives are included, a more balanced generation mix that is significantly more desirable than a cost-optimal solution to the involved stakeholders can be found. This is especially true in the first two scenarios (70% and 90% emission reduction). In the third scenario, however, the least-cost solution was quite close to the most desirable result: the costs of reducing land use, and visual impact even more are too high to be desirable. If the other objectives and stakeholder preferences were not considered, however, this could not have been shown. Therefore, including all relevant objectives is still important, even if the eventual solution might be close to a least-cost solution.

Secondly, including multiple objectives in the optimization results in the possibility to compare a set of possible solutions. This can increase the understanding of the functioning of the energy system. Through examining the Pareto-front, essential knowledge about the effects of the different elements of the energy system on the objectives is gained. It is shown that one single optimal solution does not exist: the ideal design depends on the stakeholder preferences and specific conditions in the considered regions. The full set of outcomes can be used in interaction with stakeholders as a basis for discussion. Interaction based on a set of possible solutions will be more productive than discussions based on one single optimal outcome. Unfortunately, performing a multi-objective optimization also has some drawbacks. The main drawback is that it is less clear: presenting one optimal solution as an absolute truth is more convincing than presenting a large set of possibilities that are ordered based on relative desirability. Processing a large Pareto-front is challenging, and multi-objective optimization is computationally expensive.

What is the benefit of taking a multi-actor perspective to the optimization of an energy system? This research has shown that using MCDM and comparing the views of different actors towards the optimal design can indeed be useful in analyzing the results of a multi-objective optimization. The main benefit is that this approach is an insightful way of comparing the different solutions on the Pareto-front. It can be used to identify possible conflicting views between different actors and indicates the situation to which the market will converge. In addition to this, MCDM has been used to identify one single total average optimal solution for each scenario. Identifying one optimal solution from the Pareto-front is not possible without allocating weights to the different objectives in some way. In this research, it is argued that by analyzing actor preferences, a more realistic design can be obtained.

As discussed in the previous chapter, this approach also knows some limitations. The results are quite sensitive to weights allocated to different criteria and aggregating the preferences in this way does not lead to a definitive optimal solution (as is the case for a single-objective optimization). Allocating weights a posteriori, however, is still more relevant than doing this a priori. More knowledge is gained about the functioning of the system, and the optimal outcomes for different actors can function as a basis for discussion. Although there are some limitations, MCDM has been able to provide a solution that can be acceptable to all actors: an outcome that provides a balance between different preferences is found.

What are the most important implications for policymakers from this research? From this research, it is clear that the energy transition will entail large challenges regarding spatial integration and local acceptance. The model shows that a third of all available land is required for energy generation when 98% of all emissions are to be reduced in Goeree. Large investments will be required, and policymakers should assist in the process of finding investors.

The model shows that the market, at the hands of investors, will likely converge to high shares of wind power in a future energy system. This situation will not be desirable for residents and governments because high amounts of wind energy will increase land use and visual impact. Governments may need to incentivize investors to invest in other generation methods to reduce land requirements and visual impact. Wind turbines will inevitably play a big role in a future energy system, even if land use is taken into account. Policymakers should ensure the inclusion of all stakeholders to guarantee sufficient acceptance for the wind turbines. The dependency on wind energy may be a risk and policymakers need to prepare for periods with little or no wind by having sufficient flexible capacity.

To reach a reduction in emission of 70%, a combination of wind and solar can be sufficient. This is a very positive finding: the goals for 2030 can be achieved without requiring fundamental changes in the energy system. If the share of RES-E is increased even further, some form of flexible generation or energy storage is needed. Power system planners should guarantee sustainable flexibility in the grid and should start planning for flexibility well in time. More efforts should be directed towards developing cost-effective energy storage since energy storage can significantly reduce the land requirements in a future energy system. If land use is a big concern in the region, project developers should be incentivized to install storage along with wind turbines and solar panels.

The model also shows that avoiding all emissions and becoming completely self-sufficient is possible in Goeree, but costs, land use and visual impact all increase significantly if more than 80% of the emissions are to be avoided. Although a regional scale is suitable for solving spatial integration and local acceptance issues, inter-regional cooperation will still be necessary in the future.

10.3. Recommendations for further research

Several possibilities still exist for further research. Some elements have been left out of the scope of this research, and several limitations were introduced in section 9.2. Further research can solve some of these limitations and expand on the work done in this research. This section describes some promising possibilities for further research based on this research.

The model created for this research is generic and can be applied to any region. This research opens the door to energy systems optimization from a stakeholder perspective and designing for a feasible real-world design. Only Goeree is evaluated in this research. Although the results are likely similar for another rural region, analyzing different regions to see possible differences in the optimal generation mix would be a very interesting direction of research. The model could also be used to investigate the possibilities of becoming completely self-sufficient with regards to electricity. Also, the objectives and stakeholders identified in this study are not only relevant on a regional level. Similar challenges exist on a national level. An important recommendation is to adapt the model and to apply the method proposed in this research to a national energy system.

This research uses deterministic weather and demand data for only one year. Full knowledge about the weather and demand is presumed. The effects of running the model for multiple years or including uncertainties with stochastic data would be very interesting to see. Another uncertainty that is not directly accounted for is the uncertainty in allocating the weights for MCDM. Other methods to analyze the large multi-dimensional outcomes of the multi-objective optimization, such as k-means clustering, allow a modeler to identify different scenarios from the Pareto-front without the requirement of allocating weights. This can be another interesting direction of research. Also, the performance of the genetic algorithm that was used has not been compared to other algorithms directly. Comparing the results by using a different optimization algorithm will increase the certainty that the actual Pareto-front has been found.

The scope of the model was also limited to allow for analysis. Incorporating more technologies such as long-term energy storage, Carbon Capture and Storage, and hydro energy will lead to an even better design. Also, Demand Side Management could be introduced to better match the profiles of demand and supply, which could reduce the costs, land use, and visual impacts of the energy system. This research assumes that biomass only comes from crops grown specifically for biomass. In reality, however, several waste streams may exist within the region that can supply biomass for energy without requiring land transformation. Region-specific analysis can identify these possibilities to include them in the model.

In this research, it is assumed that all electricity can be exported at any time at the national electricity price. In the future, when high shares of renewables are present, this may not be the case. Therefore, another valuable addition to this research would be to expand the way that electricity prices are modeled by incorporating the price fluctuations that will inevitably arise when high shares of renewables are introduced into the energy system.

This research provides a simplified representation of the land used for energy generation and the visual impact of wind turbines. To gain more insight, higher resolution modeling (including more nodes) combined with geographical mapping of the placement of RES-E, such as shown by Ramírez-Rosado et al. (2008), may be necessary. One can minimize the number of people directly affected by the visual impact based on such a map and provide insight into the optimal placement of RES-E, something that has not been investigated in this research. This would increase the usefulness to policymakers even more.

The most important next step based on the findings of this research, however, is to engage with the involved stakeholders. An ideal design has been proposed based on the average preference of all stakeholders, and this provides a good starting point. The actual optimal design will depend on specific conditions within the region and the views of the involved stakeholders. In a municipality where resistance against wind turbines is high, this will involve fewer wind turbines. If this issue is not as pressing, costs may be the most important factor. A feasible design can only be found after active engagement with the involved stakeholders. The knowledge gained from this interaction can also be used to improve the model. To be able to provide relevant policy advice, models need to be suited to the actual challenges policymakers face. This research intends to be a first step in this direction.

Having reflected on the conclusions and possible directions for further research, this report is hereby concluded. The findings are interesting, but new insights always lead to more questions and many challenges are still ahead. This study hopes to advance the field of energy systems modeling and bridge the gap between social studies into the social challenges involved with the energy transition and energy systems optimizations: *”big journeys start with a small step” - Lao Zi*

Personal reflection

So there it is. The end of this seemingly endless report. If you got this far, I want to thank you for reading a document that was probably not always easy to read, but has been my single focus for the past five-and-a-half months. I will use this section to reflect on how the process of writing this thesis has been and share some of the lessons I learned.

Initially, I didn't know what I wanted to research for this thesis and I came across an idea for an assignment posted by Ni. When I spoke to Ni through Skype for the first time, I had no idea of what was ahead. The energy system was somewhat new to me, but Ni seemed confident that I could complete this project and immediately gave me a lot of freedom. I was allowed to decide on the direction of the research and what kind of approach I would take. All that was clear what that it would be a multi-objective optimization for a regional energy system. I decided to approach the energy system from a rather unorthodox, more socially oriented, point of view. This may not have been the easiest path to take, but I am happy with the way it turned out.

The progress, initially, was relatively slow, but as soon as I started programming the model in Python, the research started to pick up pace and became more and more interesting. It is still fascinating to me that I was able to model an energy system from scratch and was able to draw some interesting conclusions. Just by writing some lines of code, a complex problem can be structured, and realistic predictions can be made.

Having created the model and looking at the results, it was time to start writing them down. It was at this point that I discovered that I had included so many aspects and obtained so many different results that it would not be possible to write it down in a coherent and understandable way. In the process of stripping the model and the results to something that would indeed be presentable, I had to 'kill a lot of my darlings': I had to scratch many things that I thought were very interesting, but strictly speaking, did not add anything to the story of my thesis. It made me once again realize how important it is to have a clearly formulated goal and to strip away anything that does not contribute to reaching this goal. The question of whether or not I included all relevant things but not too much has kept me occupied until the very last moment.

In the process, I found out that doing research is not always directly about solving a problem. Sometimes, it is about investigating a direction of research and seeing what is there. This really was new to me, and it was an interesting process. Because I did not always directly know what I was looking for, many days were spent exploring directions that eventually led nowhere. Even though the end result is different than I could probably have imagined, I am proud to present this work that has kept me so busy over the past period. I am incredibly grateful to have had the opportunity to make a (albeit small) contribution to the immense challenge of creating a transition in the energy system. I honestly feel that by focusing on the softer elements of minimizing land use and visual impact, energy systems optimization models can be significantly improved and that this is not just relevant on a regional level. In the future, I hope that my work, whatever it may be, will also provide a contribution to a more healthy, social, and sustainable future. For now, I am glad that my period as a student in Delft has come to an end. It has been an incredible journey, but it is only the beginning.

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A

Introducing energy neutral regions in Europe and The Netherlands

To provide some context, some regions that have already become energy neutral or have high ambitions regarding the energy transition are discussed here.

A.0.1. Energy neutral regions in Europe

In Europe, some regions such as Samsø in Denmark and Varese Ligure in Italy, started their renewable development already in the 1990s. Several examples of energy neutral regions can be found in Europe, some of the better-known ones have been shortly summarized in table A.1. It can be seen that all of the regions mentioned in table A.1 are still Grid-Connected. This means that these regions are not absolutely self-sufficient (able to fulfill their own demand at all times). The reason for this is that by staying connected to the grid, no EES or regional flexible capacity is needed since electricity can be imported from the mainland in times of shortage.

The best-known energy neutral region is Samsø in Denmark. Samsø was the first region to become completely energy neutral with regards to electricity in 2005 (Nielsen & Jørgensen, 2015) and has served as an example to regions around the world. 3700 people are supplied with energy by 21 wind turbines. Samsø wants to become completely energy self-sufficient in the future; not relying on any external energy resources even for their ferries and cars.

In recent years, sustainable development has become a key point in policy for regions throughout Europe. Among others, cities like Munich in Germany, Bourdeaux in France and Barcelona in Spain want to become completely energy neutral by 2050 (Bringault et al., 2016). This development is also taking place in The Netherlands.

A.0.2. Energy neutral regions in The Netherlands

In The Netherlands, the Regional Energy Strategy is a central part of the plans to reach the goals of the national government: regions play a key role in aligning stakeholders, solving spatial integration issues and ensuring acceptance of the energy system. In addition to the 30 regions specified in the RES, many municipalities have expressed the desire to lead in the energy transition, become less dependent on fossil fuels and to generate their own energy. Both top-down initiatives (governments setting energy targets) and bottom-up (initiatives by citizens or entrepreneurs) exist in The Netherlands. Often, a combination of the two leads to

Table A.1: Case studies of European regions that are energy neutral. SA = Stand-Alone, GC = Grid Connected

Region	Population	Area (km^2)	Renewable energy share	SA/GC	Generation method	Source
Samsø, Denmark	4.100	114	100%+	GC	Mainly wind energy	Droege (2009)
Güssing, Austria	3.900	49	100%+	GC	Biomass, Solar PV	Droege (2009)
Jämtland, Sweden	128.000	49.341	90%	GC	Mainly hydropower	Droege (2009)
El Hierro, Spain	10.400	269	70%	GC	Hydropower and wind	IRENA (2019)
Varese Ligure, Italy	2400	163	100%+	GC	Wind and Solar PV	Droege (2009)

more success.

141 municipalities in The Netherlands have set the ambition to become energy neutral (BMC, 2018) and HIER (2018) showed that almost 500 energy cooperatives have been started in the Netherlands with the aim of transforming their community or region into an energy neutral area. Some examples of regions with ambitions to become energy neutral will now be discussed.

On the island of Goeree-Overflakkee, also one of the 30 energy regions, the municipality set the ambition to be energy neutral before 2020. The municipality supports innovations and focuses on bringing down the energy demand. An energy cooperative called DeltaWind was started already in the 90s. Their aim was to completely fulfill Goeree-Overflakkee's energy demand with RES-E. Citizens can loan the cooperative a maximum of 5000 euro's and DeltaWind invests in wind energy. Citizens are paid interest and DeltaWind has already succeeded in producing enough electricity for all 15.000 households of Goeree-Overflakkee (Hufen & Koppenjan, 2015). The municipality has already indicated that the next step will be to be completely independent of the mainland for their energy supply by focusing on EES and DSM (Www.goeree-overflakkee.nl, 2019). There is no clear target for this yet, however, and it is not clear how the municipality intends on reaching this goal of absolute self-sufficiency.

The municipality of Rotterdam, with 600.000 citizens, has set the ambition to become energy neutral by 2030. They focus on cooperating with housing corporations and energy companies. They support local initiatives, such as energy cooperative 'Blijstroom' and lobby for subsidies for making houses more sustainable (Gemeente Rotterdam, 2019). The municipality focuses on wind energy and intends to be involved in the planning and wants to take the lead in involving all stakeholders in the process (Gemeente Rotterdam, 2016).

The city of Zwolle wants to be energy neutral by 2050 (Energiek, 2017). Zwolle has a population of 125.000 people and currently only 7% of the energy is from a renewable source. In Zwolle, there are also several smaller local initiatives such as the crowdfunding of 300 solar panels and initiatives from housing corporations to make houses more sustainable. Zwolle also has an energy cooperative called 'Blauwvinger'.

There are many other municipalities and regions that have set ambitions to become energy neutral, including Assen (2050), Ameland (2020), Texel (2020), Eindhoven (2045), De Fryske Marren (2030) and a combination of 13 municipalities in Twente (2050). Some municipalities are already making progress. For others, becoming energy neutral is still further away. Although many municipalities have high ambitions, some municipalities (such as Sûdwest-Fryslan) oppose the placement of wind turbines in their municipality because of the influence on the landscape and tourism (PBL, 2017, p.60).

B

Criteria that have not been included in this research

This chapter of the appendix serves as an addition to chapter 2 of this research. Criteria that were evaluated, but not used in this research are discussed here because they may be relevant to other researchers. The same categorization that was described in chapter 2 is used: the criteria are divided into economic, environmental, social and technological criteria.

B.1. Economic criteria

In this research, several economic criteria have been considered. A significant amount of other criteria has also been investigated and these are discussed here.

B.1.1. Total annual cost

Most studies that optimize for minimal cost, minimize the total annual cost (Theo et al., 2017). Although from a research perspective this is an interesting measure, it is not specifically used in this research. The total annual cost is not considered to be important by any actor. They might want to minimize investment cost, which is included in the annual cost. To accurately represents actor interests, this research uses LCOE as a cost metric.

B.1.2. Integration costs of RES-E

When looking at the integration of RES-E into the electricity system, just looking at the LCOE of the individual plants is not sufficient. A systems perspective is necessary (Hirth et al., 2015). The integration of RES-E into an energy system will also lead to some additional integration costs, which are not usually captured in models, as shown by Hirth et al. (2015). Three aspects of additional system costs can be identified.

1. Profile costs: on average, the market value of electricity generated by RES-E has a lower market value than conventional generation. This is because of the fact that the peaks in generation from RES-E tend to overlap, leading to a high supply. This effect needs to be taken into account. Investing in storage will reduce profile costs. Profile costs are included in this research, because electricity generated is sold for the real-time price. What has not been included, however, is the possibility that with higher shares of RES-E, this effect will be many times larger than can be noticed in the current electricity prices.

2. Balancing costs: the variability and unpredictability of generation by RES-E lead to a higher cycling burden on other power plants, increasing the cost of generation. The balancing costs can be reduced by improving forecasting methods. This has not been included in the scope of this research.

3. Grid costs: the integration of RES-E may demand investments in transmission and control infrastructure, which should be taken into account in the analysis. Transmission

and control are not included in the scope of this research. Therefore, grid costs are also not included.

B.1.3. Individual cost metrics

The total system cost is made up of several elements. These will now be discussed as fixed and variable costs. Fixed costs are independent of the amount of energy generated by the plant. Variable costs increase when more power is generated.

Fixed costs

1. *Capital costs* has been included in the model.
2. *Fixed Operations & Maintenance costs* (FOM) consider the fixed expenditure necessary on an annual basis to maintain and operate the system, regardless of the amount of electricity generated. Investors will also consider high FOM to be a risk. If there are high fixed annual costs, significant production is needed to reach a break-even point. In this research, however, FOM has been included in the LCOE and is not considered as a separate criterion.
3. *Costs of subsidies* consider the costs incurred by governments by subsidizing energy projects. Subsidies for big energy projects are going down. In 218, construction was started for the first unsubsidized offshore wind energy park in The Netherlands (Technology Review, 2018). Although this criterion is interesting from the standpoint of the national government, this criterion is hard to capture in a model. Subsidies are determined for each individual project by putting out tenders for big energy projects. Simply put: commercial parties can bid on the project and the bid that demands the least amount of subsidy gets the contract. This does not only depend on the composition of the generation mix, but also on many contextual factors. Modeling this is beyond the scope of this report.

Variable costs

1. *Variable Operations & Maintenance costs* (VOM) are measured per MWh and represent the cost required to generate one MWh of electrical energy. It includes the cost of the resources (fuel) required to generate one MWh of electrical energy and all other operational costs necessary. No actor specifically wants to minimize VOM, as long as the (total) LCOE is competitive.
2. *External costs* are often overlooked. External costs represent all the costs incurred by society as a result of the operation of the electricity system. It may include damages to ecosystems and even the possible effects on property value, but most researchers focus mainly on the external costs of emissions such as CO_2 and methane (Alnatheer, 2005; Mathiesen et al., 2011). Governments will want to minimize these external costs to society. In this research, external cost will not be taken into account. CO2 emissions are considered separately. Evaluating external cost would be specifically useful if one wants to aggregate all outcomes into a cost figure, which is not the aim of this research.

B.1.4. Metrics for the attractiveness of an investment

In this research, LCOE is used to measure the attractiveness of an investment. IRR was found to be perfectly correlated with LCOE. The IRR, however, is not the only available tool. Capital budgeting is a field of research in itself, so only an overview can be provided here, but some of the other most relevant metrics for investment appraisal will now be discussed. From further investigation, it was concluded that all of these values are highly correlated with IRR and therefore with LCOE.

Equivalent Annual Annuity

Both NPV and IRR are usually used to compare different investments with a similar life-time. An energy system, of course, does not consist of one investment. It is a combination of many smaller projects. All generation methods included in this research have a similar life-time, making NPV and IRR a suitable method to analyze the attractiveness of the investments. If life-times are not similar, *Equivalent Annual Annuity* (EAA) can be used to compare the investments. EAA calculates the annual payment leading to the projects NPV if it was a fixed yearly payment:

$$\text{EAA} = \frac{\text{NPV} * r}{1 - (1 + r)^{-n}} \tag{B.1}$$

Where r is the interest rate and n is the lifetime of the investment. The EAA values for each investment can subsequently be summed to find the total EAA.

Return on Investment

Return On Investment (ROI) is a relatively simple and intuitive metric for assessing the profitability of an investment. The total discounted profit from the investment(s) is compared to the initial investment. A higher rate of return means that a similar investment returns a higher profit.

One can calculate the total discounted profit from a project by dividing the NPV by the initial investment:

It is calculated by:

$$\text{ROI} = \frac{\text{NPV}}{CapEx} \tag{B.2}$$

A high ROI is strongly correlated with a high IRR (and low lCOE). Therefore, it is not included in this research.

Accounting Rate of Return

The Accounting Rate of Return (ARR) can also be used to compare different investments. It is calculated by taking:

$$\text{ARR} = \frac{\text{Annual Profits}}{CapEx} \tag{B.3}$$

The fraction between yearly profits and the investment is calculated. A high Arr is almost perfectly correlated with a high IRR. Therefore, it is not used in this research.

Payback period of the investment

The payback period of the investment can also be used to determine the attractiveness of an investment. Investors will favor a lower payback period. The payback period is calculated by dividing the investment costs by the expected annual profits. Usually, this metric is used to analyze one project. It can also be used, however, to determine the total payback period for the entire system. Producers and cooperatives will want to minimize the payback period. It was found, however, that there is a very strong correlation between payback period and IRR (of around 0.95). For this reason, it is not included in this research.

Risk of investment

The investor's choice on whether or not to invest in a certain project is the result of a consideration of the return on the investment and the (perceived) risk involved (Wüstenhagen & Menichetti, 2012). High risk on investment means a higher cost of capital. RES-E is relatively capital intensive compared to conventional electricity generation. A high cost of capital would be a big barrier for the transition to RES-E (Hirth & Christoph, 2016). Investors into RES-E are, therefore, even more sensitive to risk than investors into conventional generation (Schmidt, 2014). Investment risk for RES-E can have two sources. Project development risk includes risks regarding the siting of the project and receiving permits. Income risk includes uncertainty in the amount of energy that will be generated and risk resulting from fluctuating energy prices (O'Boyle, 2018; Bhattacharya & Kojima, 2012). Bhattacharya & Kojima (2012) performed a promising study analyzing the risk of an energy generation portfolio by looking at the year to year variation in generation costs. Analyzing the risk of different energy portfolios should be a bigger part in energy systems modelling. In general, however, the risk of investment into RES-E depends on many contextual and behavioral factors (Wüstenhagen & Menichetti, 2012) and assessing the risk involved in different energy portfolios is beyond the scope of this research. Out of all considered criteria in this appendix, the risk of investment is most likely to influence the investment decision and the composition of the generation mix. Therefore, investigating the risk of investment for different technologies (e.g. by looking at the percentage of projects that fail) may be an interesting direction for further research. However, it is not expected that this significantly impacts the results, because the local resistance against RES-E is taken into account in this research and this is one of the main factors influencing the risk of investment (Wentink, 2019).

B.2. Environmental criteria

The energy system affects the environment in several ways. The most documented environmental effects concern the emissions of different energy technologies.

B.2.1. Emissions and pollution

Several emissions play an important role because of their negative effects on the environment. CO_2 is considered in this research, but it is not the only gas that is emitted by the energy system:

1. Methane (CH_4) is another important greenhouse gas which contributes to global warming. Methane emissions should be minimized.

2. SO_x and NO_x are also polluting gasses that contribute to air pollution and acidification.

These emissions have not been taken into account, because in most objectives of the different actors, only CO_2 is included. In future research, it would be an interesting option to evaluate the other emissions as CO_2-equivalents, such as by Pehnt (2006). This allows the modeller to aggregate all emissions to one number. It was estimated not to have a big impact on the results, therefore it is left out of the scope of this research.

Most studies focus on analyzing the emissions from the operation of the electricity system. Another valuable perspective, however, may be to analyze the emissions based on a Life-Cycle Analysis (LCA). When calculating the emissions based on an LCA, emissions for the entire life-cycle of the energy system are accounted for (including material production, construction etc.). Wind turbines and Solar PV generation do not emit anything during operation. Wind turbines and solar panels, however, also need to be produced, transported, and constructed. Emissions cannot be avoided completely in this process. A Life-Cycle perspective was not expected to have a significant influence on the results and has been left out of the scope of this research.

B.2.2. Other environmental impacts

Those who oppose the placement of wind turbines often argue that wind turbines are detrimental to bird and bat populations. In this research, the effect of wind turbines and bats are not taken into account. If sufficient mitigation measures are applied, the effects of wind turbines on bird population is much smaller than the effects of conventional electricity generation (Drewitt & Langston, 2006; Sovacool, 2009). The effects on wildlife and habitat have also not been taken into account. RES-E overall have positive effects on wildlife compared to conventional generation and if enough care is taken to protect nature and habitats of protected species, the effects will be minimal. Several other environmental effects, such as smog creation and effects on groundwater quality, were found to be less relevant to this research.

B.3. Social impacts of energy systems

The fourth and final category of impacts that will be discussed are the social impacts of energy systems. Social impacts are often hard to quantify and sometimes overlooked in modelling (Pasqualetti, 2011). Several different social impacts will now be discussed.

B.3.1. Competition of energy production with food production

In The Netherlands, a lot of land is used for food production. Most of the new installations of onshore RES-E will also be placed on farmland. With wind turbines, the land between the turbines can still be used for the production of food. The production of biomass feedstock, on the other hand, competes directly with the production of food. The placement of solar PV may also use up some land that is currently used for agriculture. Competition with food production may be a significant issue, specifically in poorer countries (Nonhebel, 2005). In this research, however, it is left out because it is not a specific objective for any of the actors.

B.3.2. Impact on local residents

Visual impact on residents is a criterion that is taken into account in this research. This is, however, not the only impact that the energy system has on residents. Several other effects of the placement of RES-E are:

1. Those living very close to a wind turbine may experience a 'swooshing' **noise** from the blades of the turbine. Because the level of annoyance from this noise is closely linked with the perception of the visual impact of the wind turbine (Pedersen et al., 2009), noise is left out of the scope of this research.
2. Some members of the public fear a negative effect of RES-E on **property value** for the surroundings of the RES-E (Vyn & Mccullough, 2014). Research has shown that this perception is closely linked with the overall perception of RES-E and statistical evidence for an effect on property value has not been found (Vyn & Mccullough, 2014; Hoen et al., 2009). Therefore, in this research, property value has not been taken into account.

B.3.3. Job creation

Engelken et al. (2016) found that job creation is an important driver driving municipalities towards pursuing self-sufficiency. Studies that investigated job creation by the implementation of RES-E found that overall, renewable generation is more labour intensive than conventional electricity generation (Del Rio & Burguillo, 2008). Meyer & Sommer (2016) conducted a literature review of studies analyzing the number of jobs created per MW for different generation technologies. They found that results differ a lot per case based on the location of the RES-E and the methodologies and assumptions used in the different studies. Some studies, for instance, only look at direct job creation from the construction and operation of RES-E. Others also take jobs that are created indirectly into account. Another difficulty is that not all jobs will be created within the region studied; they can also be created outside of the region. Most regions will not have their own companies that build wind turbines or are specialized in the installation of PV installations. Also, the number of jobs created will likely not depend mostly on the composition of the generation mix but on other, contextual, factors. Therefore, job creation is not considered in this research.

B.3.4. Other social factors

Some regions that aim for a quick energy transition intend to achieve *a contribution to social cohesion, an increase in tourism as a result of the developments and possible effects on income distribution* (Del Rio & Burguillo, 2009). These factors are hard to quantify and predict. These factors are not expected to be crucial considerations in choosing between different technologies. Other (contextual) factors are more important in determining, for instance, the effect of the energy system on social cohesion than the composition of the generation mix. Therefore, they will not be discussed further. *Health and safety effects* of the energy system might also be important when comparing alternatives for an energy system. It is usually measured in years of life lost. Although switching to RES-E will bring significant health benefits (Pasqualetti, 2011; Köne & Büke, 2007), it is not the focus of this study. It is mainly relevant when analyzing the effects of conventional generation and has therefore been left out of the scope of this research. Also, governments and energy cooperatives aim to increase the *public ownership of RES-E*. Whether or not they are successful in reaching this goal, however, does not depend on the composition of the generation mix, but on other factors. Therefore this is not taken into account in this research.

B.4. Technological criteria

Technological criteria have been split up into criteria relevant for a stand-alone system, for a grid-connected system and for both a stand-alone and a grid-connected system. First, the criteria relevant to a stand-alone system will be discussed.

B.4.1. Technological criteria relevant for a stand-alone system

Some criteria are only relevant for a regional energy system that operates in an isolated, stand-alone, manner. This research does not consider a system that is purely stand-alone, because this is not a realistic scenario for an entire region in The Netherlands. There will always be a connection to the grid. A stand-alone system has a high renewable energy share. Flexibility can be provided by biomass, diesel generators or by the curtailment of wind turbines. The most important technological criteria for a stand-alone energy system is its ability to provide electricity reliably.

Reliability of power supply

Tezer & Yaman (2017) defined the reliability of the system as: "capability of the power system to provide supply of electrical energy to the customers in an adequate and secure way". The reliability of the power supply is an essential criterion when designing an electricity system that operates as a stand-alone system. In section 2.2 it was determined that most actors are concerned with guaranteeing a reliable power supply. Power outages in modern societies have huge consequences on many aspects of society (Lopes et al., 2006). Governments want to prevent this, and consumers also want to prevent this. If the system operates in a stand-alone manner, it must be capable of providing sufficient power all the time. If the system operates in a grid-connected manner, the reliability is not relevant, since energy shortages can be imported from the central grid.

Although no universal measure for the reliability of the power supply exists throughout literature, there are two basic ways of measuring the reliability of the power supply: measuring the unmet load or the number of hours that the load could not be met. Different names exist in literature and are used interchangeably, not always pointing to the same exact measure. An overview is provided by Al-falahi et al. (2017, p.258). Here, the distinctions Loss of Load Probability (LLP) is used.

LLP represents the expected amount of time that the energy supply is insufficient compared to the total time. It is given by:

$$LLP = \frac{\sum_{t=1}^{t=T} T_{\text{Deficit}}(t)}{T} \tag{B.4}$$

Where:

$$T_{\text{Deficit}}(t) = \begin{cases} 1, & \text{if } E_{\text{Deficit}}(t) > 0 \\ 0, & \text{otherwise} \end{cases} \tag{B.5}$$

An LLP of 0 means that the demand is met 100% of the time. If it is 1, there is not one hour in which the energy demand has been fulfilled. The most relaxed standard in Europe is to have an LLP of 0.1% (8 hours in a year on average) (European Comission, 2016, p. 60). This means that in 99.9% of the times, there cannot be any power shortages. If the modeller chooses to use probabilistic weather data instead of deterministic weather data, the LLP is calculated based on probabilistic values. For example, see Abedi et al. (2012). In this research, deterministic weather data will be used, so this is not relevant.

Peak-load response: Back-up capacity

The peak-load response represents the ability of the system to handle large temporal variations in demand. This is an essential attribute to a stand-alone regional power system, since large variations may occur and these cannot lead to power shortage. In literature, it is usually defined in qualitative terms by giving a certain score (usually from 0 to 5) to different technologies (Antunes & Henriques, 2016). Conventional (flexible resources) receive a high score, RES-E receive lower scores. Examples of this can be found in Diakoulaki & Karangelis (2007) and Streimikiene et al. (2012). This does not seem like a particularly reliable way of designing an energy system.

A possible way to quantify this would be to analyze the back-up power available (from storage or other flexible, directly deploy-able, sources) at any point in time as a percentage of the demand at that moment. This back-up capacity is a measure for how well the system would be able to respond to peak-loads.

$$\text{Back-up capacity}(t) = \frac{\text{Capacity not used(t)}}{E_{\text{Demand}}(t)} = \frac{\text{Curtailed generation + available storage (t)}}{E_{\text{Demand}}(t)} \tag{B.6}$$

This formula gives the back-up capacity available at any point in time. It is a time-series. If one takes the minimum of this series, the minimal back-up capacity is found. It is clear that, if a constraint is set for the stand-alone energy system to have a certain amount of back-up capacity at all times, this means that the LLP will be equal to 1. No power losses are expected, but back-up power is available for possible peaks in demand or drops in supply.

Integration of RES-E into the system

Perfect integration of RES-E into the system would mean that all of the available energy production capacity is also used in the system. Sometimes, however, there may be more production that can be used or stored by the system.

In a stand-alone system with no connection to a central grid, excess electricity generation cannot be exported. This means that turbines will have to be curtailed. This is not desirable and should be prevented (Ogunjuyigbe et al., 2016; Perera et al., 2013).

Østergaard (2015) proposes a measure for the integration of RES-E into the system:

$$\text{RES-E integration} = 1 - \frac{\text{Curtailed RES-E production}}{\text{Total RES-E production}} \tag{B.7}$$

An integration coefficient of 1 would mean that all the capacity is used. A coefficient of 0, would mean that none of the available production capacity is used. It can be argued, however, that a high integration coefficient is not necessarily a goal in itself: the excess capacity will also be represented in the system cost and other criteria such as land used for RES-E.

B.4.2. Technological criteria relevant for a grid-connected system

Amount of energy imported

The amount of imported energy compared to the total energy consumption is a measure for how self-sufficient a region actually is: how much energy cannot be produced in the region and needs to be imported. In this research, imported energy has not been considered as a criterion. The reason for this is that minimizing the amounts of imported energy is a means to the end of reducing CO_2 emissions: imported energy is not (or mostly not) generated by RES-E and generating 'grey' energy creates high emissions.

It is important to note that the amount of energy to be imported, can never exceed the critical import capacity of the transmission lines. If this limit is exceeded, not enough energy can be imported to fulfill demand (Østergaard, 2009). In practice, this will not be a great issue for a region in The Netherlands, since most regions currently import most of their energy.

Amount of energy exported

The amount of energy exported is the energy generated that cannot be used or stored within the system. More export might mean that the integration of RES-E into the system is not as good: the supply and demand profiles are not perfectly matched. Export of renewable energy, however, is not a bad thing. It means that renewable energy is used elsewhere. None of the actors has a specific objective to minimize the amount of energy exported. Therefore, it will not be taken into account. One important aspect of the export that could be taken into account in further research, is that the amount of export cannot exceed the critical export level. If the transmission lines cannot handle the export, production units may have to be curtailed.

B.4.3. Annual energy balance

An often-used metric when people talk about energy neutral regions is the annual energy balance in the region. The annual energy balance can be calculated as:

$$\text{Annual Energy Balance} = \frac{\sum_{t=1}^{t=T} E_{\text{Production}}(t)}{\sum_{t=1}^{t=T} E_{\text{Demand}}(t)} \tag{B.8}$$

If the energy balance is bigger than 1, more energy is produced than used in the region on an annual basis. Annual balance is not taken into account in this research, because having a positive annual balance is a means to the end of reducing the CO_2 emissions. Also, by calculating the annual balance, the problem is oversimplified. It is only a metric for the generated electricity and does not say anything about how well renewable energy supply and demand are matched in the region.

B.4.4. Technological criteria relevant to both stand-alone and grid-connected systems

Renewable energy share

A metric often seen in literature is the so-called *renewable energy share*. In this research, all the energy produced in the region is produced by RES-E. Therefore, the renewable energy share is practically equivalent to the reduction in emissions: only the imported energy emits a significant amount of CO_2. Increasing the amount of renewables in the generation mix is a means to the end of reducing the emissions.

Some researchers calculate the renewable energy share as a percentage of the Primary Energy Supply (PES). Some difficulties exist, however, in translating the PES of RES-E into fuel equivalents as discussed by Østergaard (2009).

Local technical know-how

Local technical know-how is important to analyze the feasibility of certain solution considered (Antunes & Henriques, 2016). It will also be attractive to a municipality to choose a certain solution for which there is more local technical know-how to maximize the chances of local companies being involved in the construction and exploitation of RES-E projects. It is usually used to compare different technologies directly to each other, and it is measured on a qualitative scale (usually by giving a score from 0 to 5) (Antunes & Henriques, 2016). A solution could be to look at initiatives that are already present in a certain region, such as a big energy cooperative focusing on wind energy and to take their knowledge into account. Talking to experts in the region may be another way to rank the different alternatives. This is beyond the scope of this research. Therefore, it has not been included.

Other technological criteria

Several technological criteria are widely used in literature, but were found not to be relevant to this research. *Energy efficiency* is the most widely used technological criterion (Antunes & Henriques, 2016). It describes the efficiency of energy conversion. For this research, it is, however, not relevant to know how much of the energy from the sun or wind has been converted into electricity. *Risk of failure* is another criterion that is sometimes used. It is used to compare different alternatives based on the number of failures in a certain period. It will not be part of the scope of this research, because this is not estimated to have a huge impact on the optimal generation mix. *Durability* of a solution describes the lifetime of the energy system. It is not relevant for this research. Both solar panels and wind turbines have a lifetime of about 25 years (Hong et al., 2013). *Maturity of the technology* is a qualitative measure used to rank alternatives based on their stages of development. In this research, only technologies that are already sufficiently developed to be used commercially will be considered. Therefore, this criterion is irrelevant.

C Testing the influence of strict constraints

In section 5.2.2, the constraints for the model have been defined by using a 'less-than' condition. This is not common practice in optimizations. Typically, 'less-than-or-equal-to' conditions are used because at the edges of the solution space is where interesting results can be found. In the future, it is advised that the model is adjusted using the 'less-than-or-equal-to' condition in the constraints.

Although this would be a better way of defining the model, the effects are not expected to be large. In this research, the average optimal result is not near most of the edges of the solution space: it is an average solution that presents the best trade-off between different criteria. The only constraint that directly influences the total average optimal solution is the constraint on emissions. The other constraints indirectly affect the total average optimal result because the total set of solutions may be very slightly shifted onto the edges of the solution space. This expectation has been tested for the second scenario (reducing emissions by 90%). The solutions are shown in figure C.1.

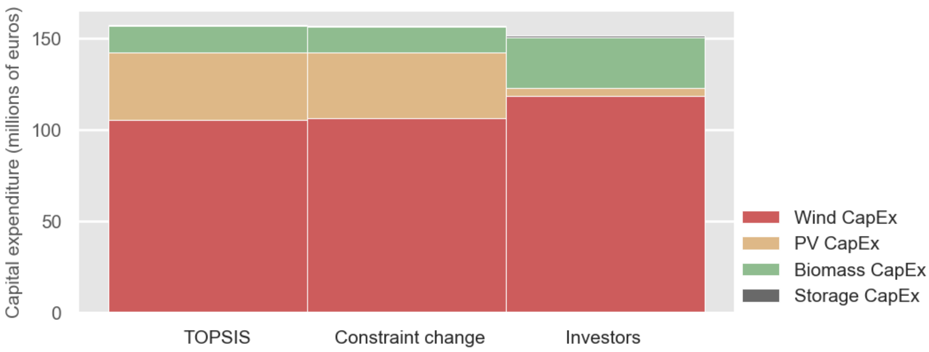


Figure C.1: Testing the effect of changing the constraints defined in the model. The total average optimal result found in this research (TOPSIS) is compared to the results with changed constraints (Constraint change) and the optimal result for the investors found in the research.

From this figure, it is clear that the results are indeed very similar. Some difference, however, can be seen. There are two causes for this slight difference. The first explanation is the fact that the results will be slightly different for each run, because the genetic algorithm is stochastic and the population size (3000) is not able to completely cover the hypersurface spanned by the Pareto-front. The second explanation is that the constraint on emissions is changed from reducing emissions by at least 90% to reducing emissions by 90% or more. This may result in a slightly cheaper solution. The first explanation, however, is expected to have the greatest influence. In the original situation, reducing emissions by 90.001% would also have been sufficient, so the difference is very slight. Even though the results are similar, it is still advised to use 'less-than-or-equal-to' constraints because of the reasons mentioned in the first paragraph of this section.

D
Comparison between optimization results for two different sets of objectives

From section 5.2.3 it is clear that Land Use and LCOE need to be included as objectives. Since only three objectives can be included, a choice between including CapEx or VIA as a third objective needs to be made. Both alternatives have been investigated. The results are compared here. The optimization is done for an emission reduction of 98%. From a general inspection of the results, shown in figure D.1 and D.2, the results can be seen to be (at least visually) similar in nature. Because the results look similar, the decision on whether to include CapEx and VIA is made by comparing the results for the values for CapEx and VIA. The values for CapEx and VIA of the two different optimizations are shown in figure D.3a and D.3b.

From table D.1, which show the results of the two optimizations for VIA and CapEx, it can be seen that the minimal CapEx is not reduced by much (only 1%) when it is included as an objective. The minimal visually impacted area, however, increases by 13%. A similar picture was seen in the other two scenarios (for 70% and 90% emission reduction).

For this reason, it is concluded that including VIA will have a bigger effect on the final result and will lead to more desirable outcomes to the stakeholders. Therefore, VIA is included instead of CapEx as an objective together with LCOE and land use.

Table D.1: Difference in result for including CapEx or Visually Impacted Area (VIA) in the optimization as a third objective

		Third objective	
		VIA	*CapEx*
Value	*VIA (km^2)*	1047	1179 (+13%)
	CapEx (millions of euro)	267	264 (-1%)

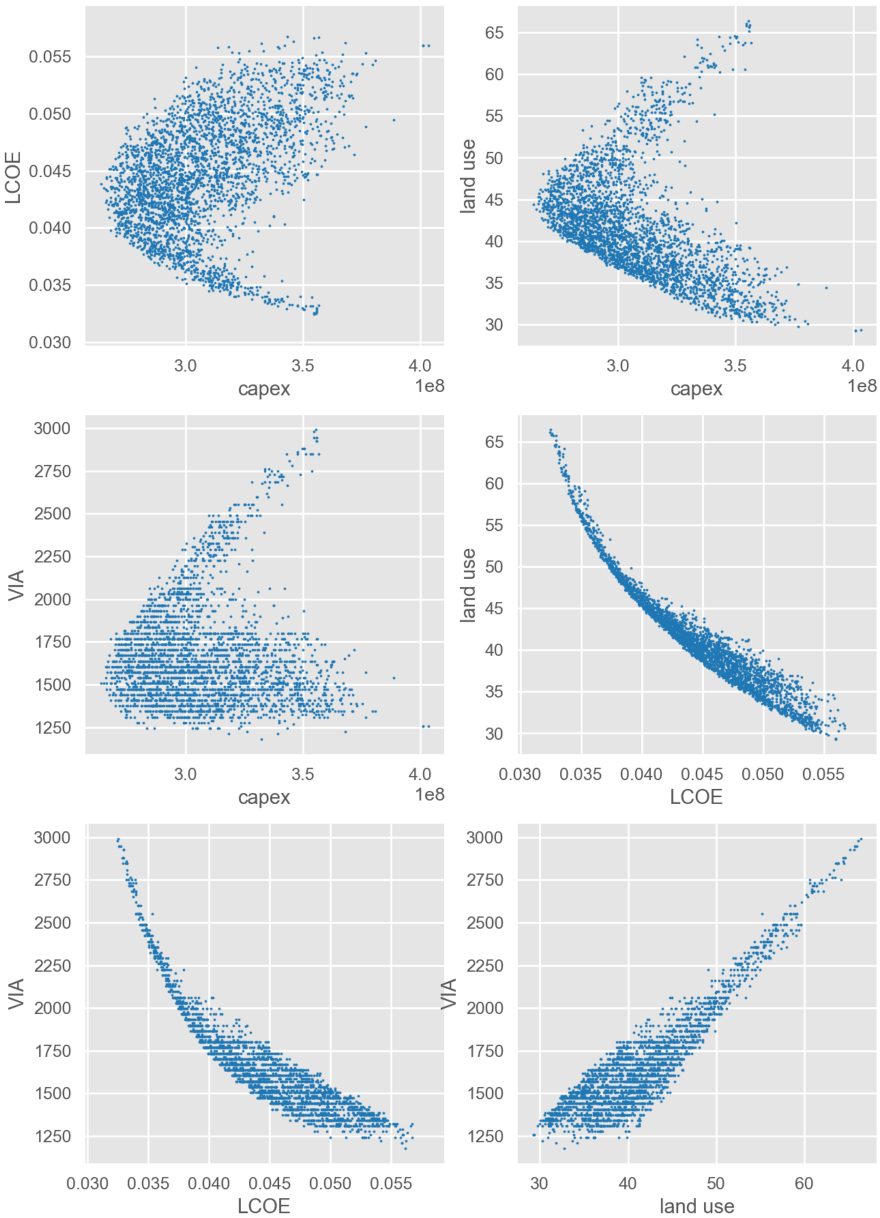


Figure D.1: Trade off between criteria when optimizing for LCOE, land use and CapEx.

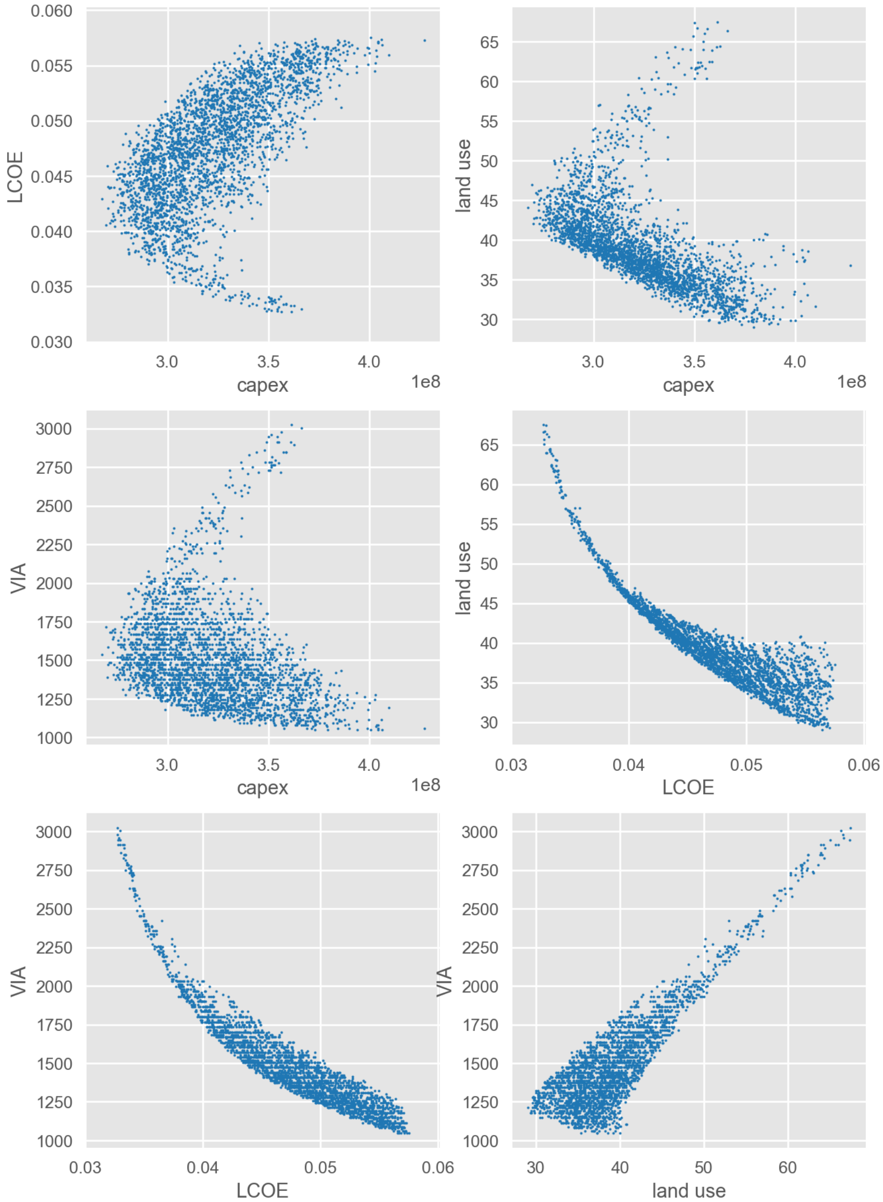
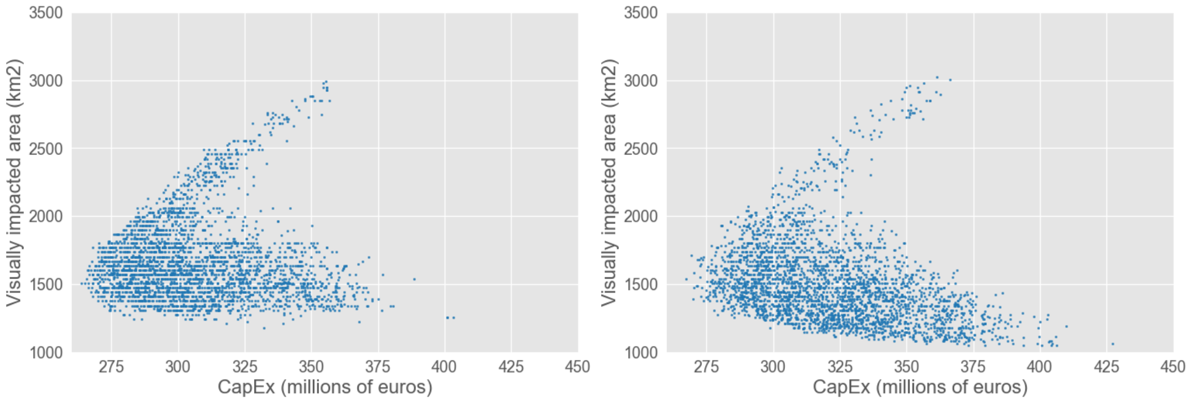


Figure D.2: Trade off between criteria when optimizing for LCOE, land use and VIA.



(a) ***(b)***

Figure D.3: (a) Results for CapEx and VIA values of optimization for LCOE, Land Use, and CapEx (b) Results for CapEx and VIA values of optimization for LCOE, Land Use, and VIA

E
Additional optimization results

E.1. Optimization for emissions and other individual criteria

In section 6.5, the trade-off between minimizing CO_2 emissions and the other individual criteria is shown. Figure E.1 shows the results for a two-objective optimization for minimizing CO_2 emissions and LCOE. No results are found for over 94% emission reduction. Minimal LCOE can be achieved with building only big (V110) wind turbines. Emissions cannot be reduced any more than 94% with only wind turbines due to periods of little or no wind. Other generation methods are required, increasing the LCOE.

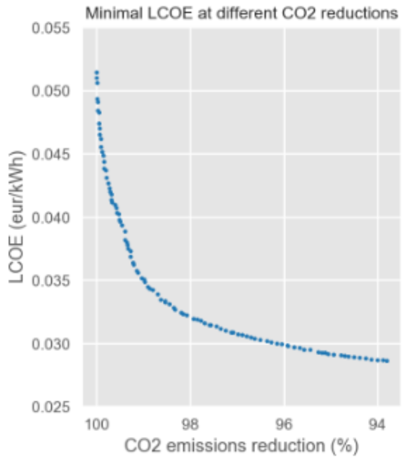


Figure E.1: Evaluating the trade-off between reducing CO_2 emissions and LCOE.

E.2. Analyzing the effect of the composition of the generation mix on the objectives

In section 7.2, the effect of wind energy on CapEx and the effect of energy storage on land use are shown. Here, all results are shown. For each of the four criteria, the effect of the different technologies is shown. The main conclusions can be summarized for each criterion:

- **CapEx:** A clear pattern is visible in the relation between wind and solar energy and CapEx. From this pattern, it can be inferred that the ratio between wind and solar is an important determinant for CapEx. Including more biomass also results in a lower capital cost. The investment costs for biomass are lower than the investment costs for the other generation methods. Storage has a negative effect on CapEx: it is quite expensive.
- **LCOE:** a comparable pattern emerges when looking at LCOE: the ratio between wind and solar has a strong effect on LCOE. More wind leads to a lower LCOE, because wind

energy is cheaper. Here, there is no optimum because it is assumed that all energy that is generated can also be sold. More wind energy means that there is more cheap energy. There is no clear correlation between the amount of biomass and LCOE: LCOE seems to be independent of the amount of biomass in the generation mix. More storage leads to a higher LCOE. This is a clear effect: there are costs involved in installing storage, but no energy is added to the system, leading to higher LCOE.

- **Land use:** the plots analyzing land use lead to an interesting observation. At 70% emission reduction, biomass is the biggest determinant for land use. At 90% and 98% emission reduction, the ratio between wind and solar is most important: more wind leads to more land use. As was explained in section 7.2, storage reduces land use at higher levels of emission reductions: there are no solutions in the set of outcomes that have low land use and low storage.
- **Visually Impacted Area (VIA):** the amount of wind energy is the biggest determinant for VIA. More wind turbines result in a higher VIA. Interestingly, the results show that solar energy can replace wind turbines (leading to less VIA), but biomass and storage cannot (there is less influence on VIA). e

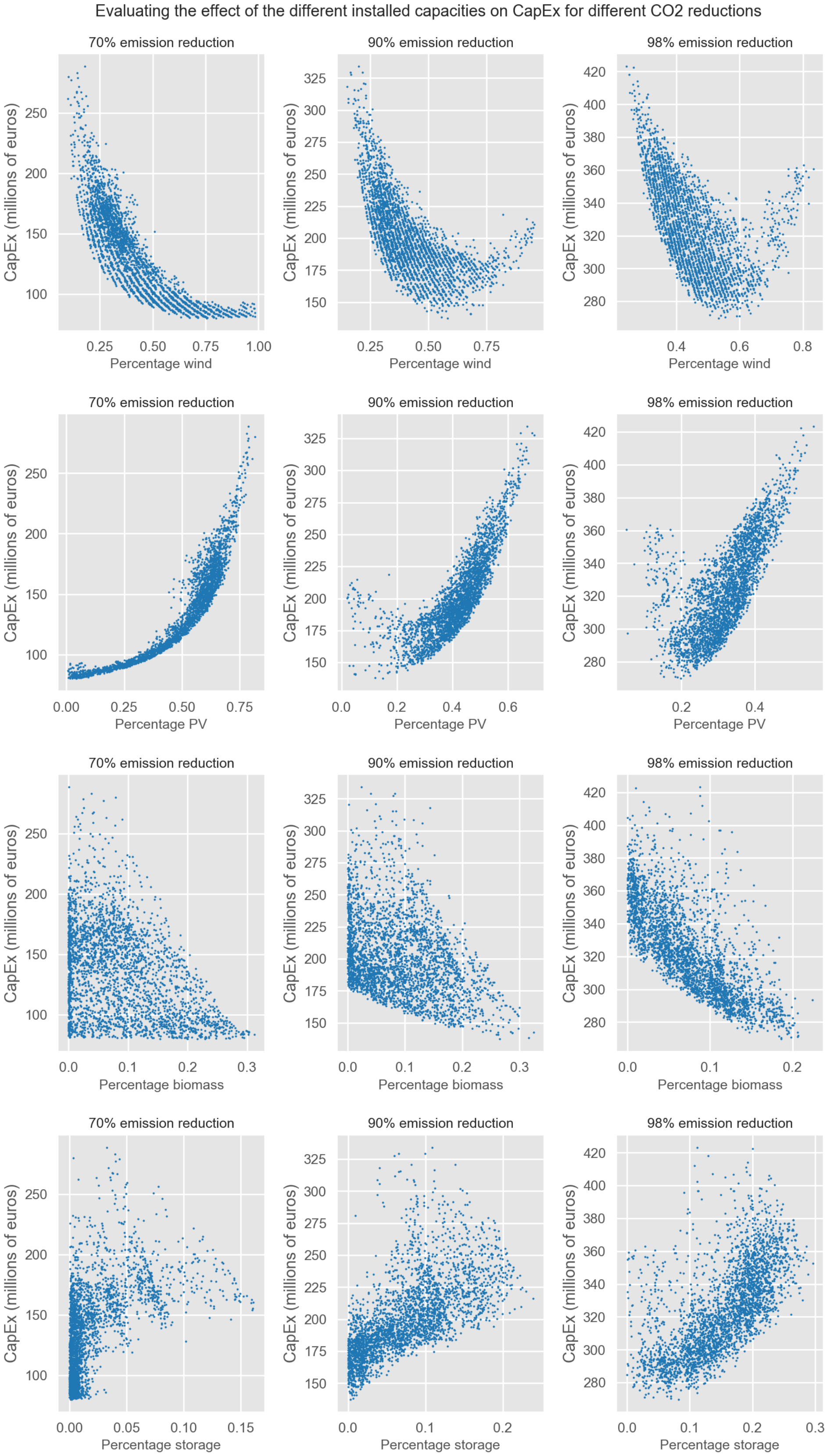


Figure E.2: Visualization of the effect of the different elements of the generation mix on CapEx.

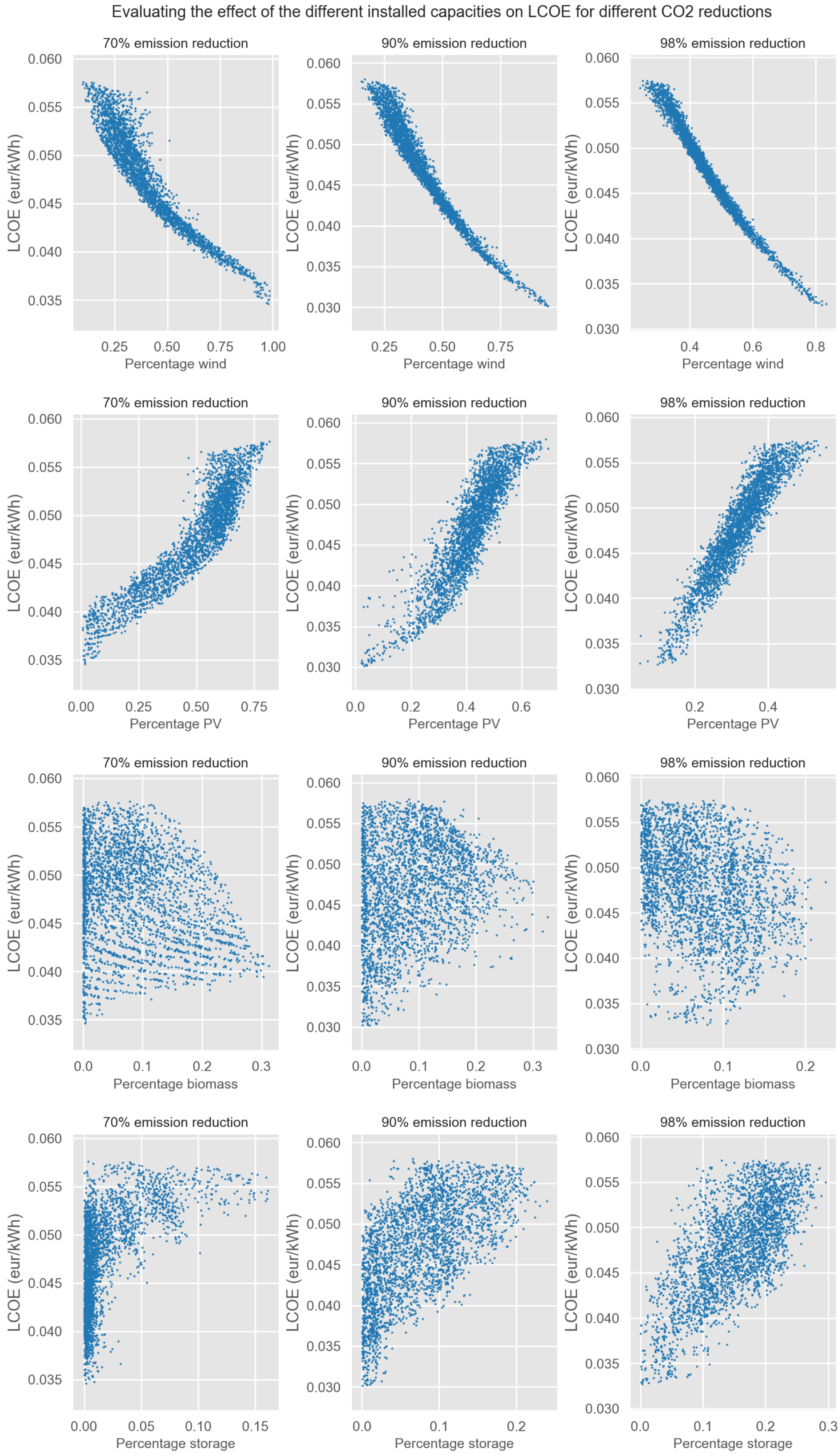


Figure E.3: Visualization of the effect of the different elements of the generation mix on LCOE.

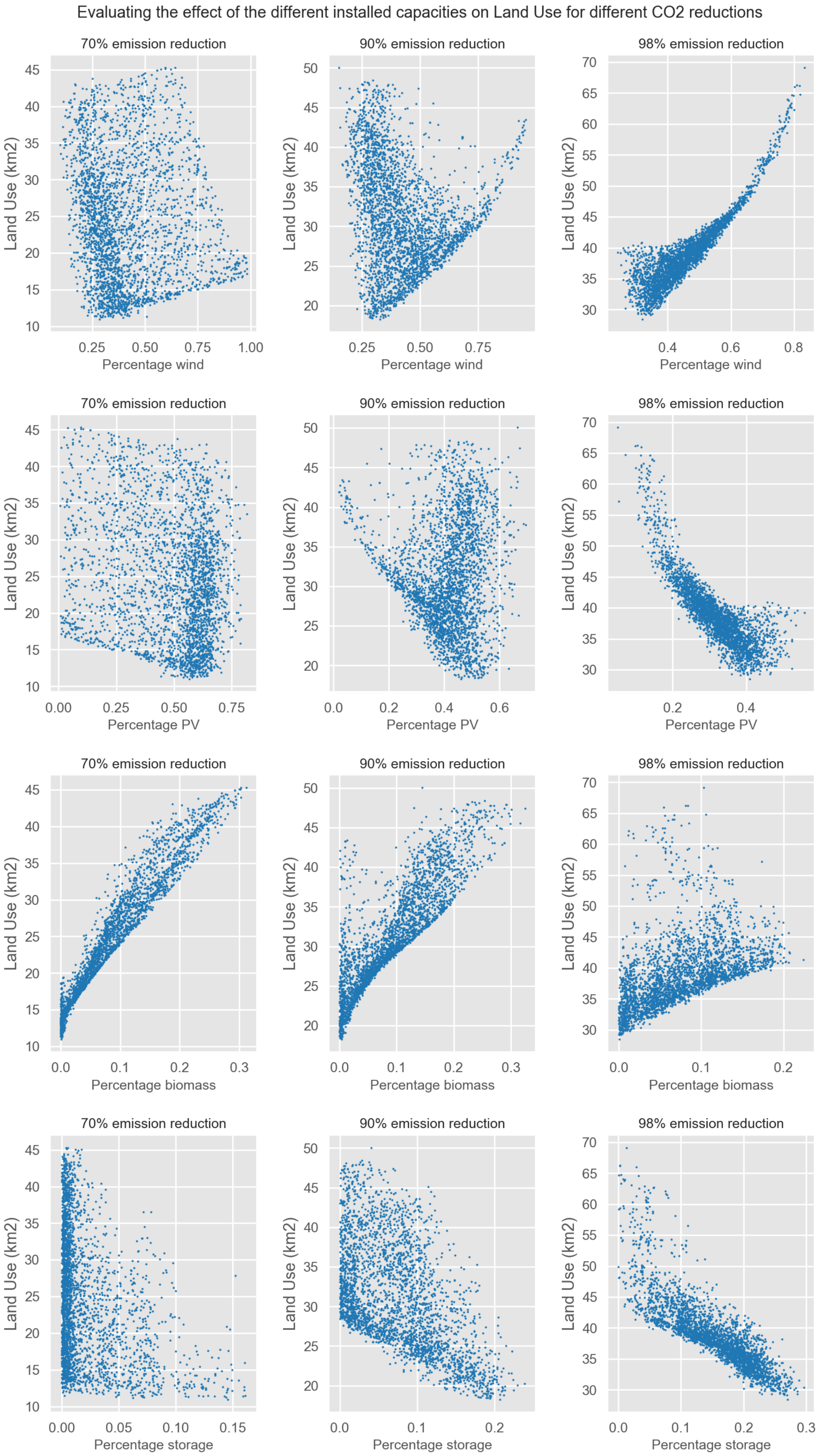


Figure E.4: Visualization of the effect of the different elements of the generation mix on Land Use.

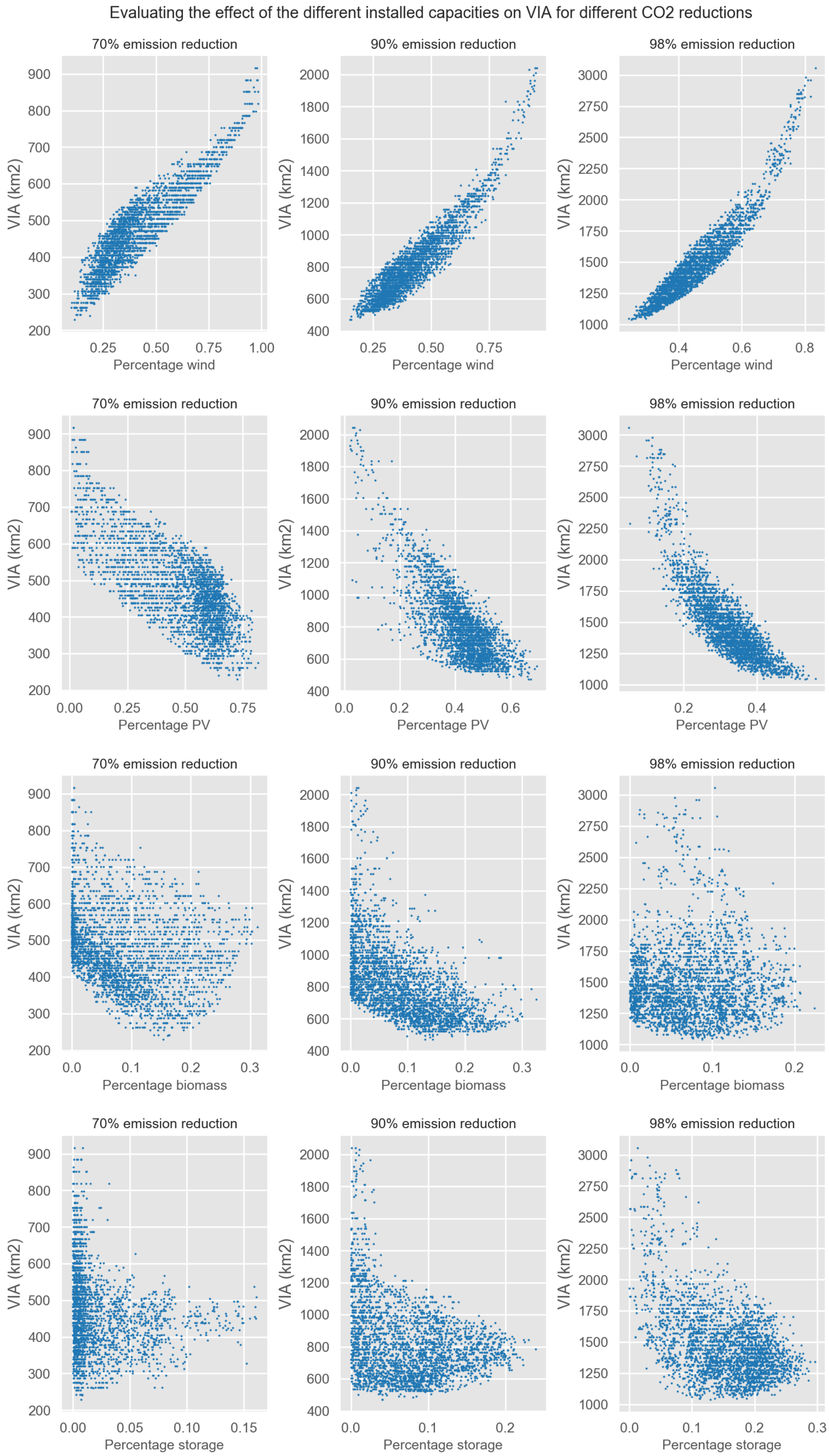


Figure E.5: Visualization of the effect of the different elements of the generation mix on VIA.

E.3. Trade-off between the different criteria in each scenario

In section 7.3 the trade-offs between CapEx & land use and LCOE & VIA was already shown. In this section of the appendix, the other criteria will also be plotted against each other for completeness.

Figure E.6 shows the relation between CapEx and LCOE. It can be seen that for the 70% reduction scenario, the CapEx and LCOE are closely related. For the other two scenarios, an interesting effect can be noticed. A lower LCOE corresponds to a lower CapEx, but only up to a certain point. If a lower LCOE than 0.04 €/kWh is desired, this can only be done by installing big wind turbines. To correct for the intermittency, a significant overcapacity is necessary. This leads to a higher CapEx: a balance between wind and other generation methods is optimal regarding CapEx.

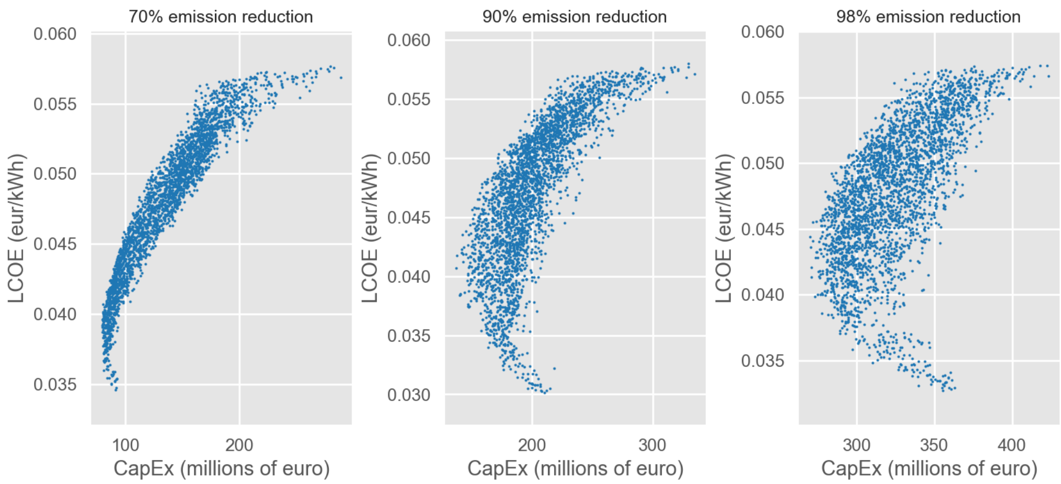


Figure E.6: Evaluating the trade-off between LCOE and CapEx. Although there is a relation between these two economic metrics, they are not perfectly correlated.

The trade-off between LCOE and land use is shown in figure E.7. It is interesting to see that in the 70% reduction scenario, many options exist and LCOE and land use are not correlated. For the scenario of 98% CO_2 reduction, LCOE, and land use are very clearly (negatively) correlated. Especially for higher CO_2 reductions, there is a very clear trade-off between LCOE and land use: the cheapest energy comes at a high cost for land use. At 98% CO2 reduction, the lowest LCOE can only be reached by having a very large overcapacity in wind turbines. This creates a high land use. In general, it is clear that very competitive energy prices can be reached with RES-E. Grid energy is provided at an average price of around 0.052 €/MWh. Many solutions are found with a lower average energy price. Also, all solutions provide a feasible investment because of the constraint on IRR.

In figure E.8, the criteria regarding land use and VIA are plotted against each other. In the first scenario, a significant trade-off exists between VIA and land use. At higher levels of emission reduction, the results show that there is a more positive relation between land use and VIA. This can be expected. Figure E.4 already showed that in the second and third scenario, the share of wind energy is the biggest factor influencing land use.

The relation between CapEx and VIA is shown in figure E.9. It shows a clear trade-off: CapEx cannot be minimized without building a significant amount of wind turbines.

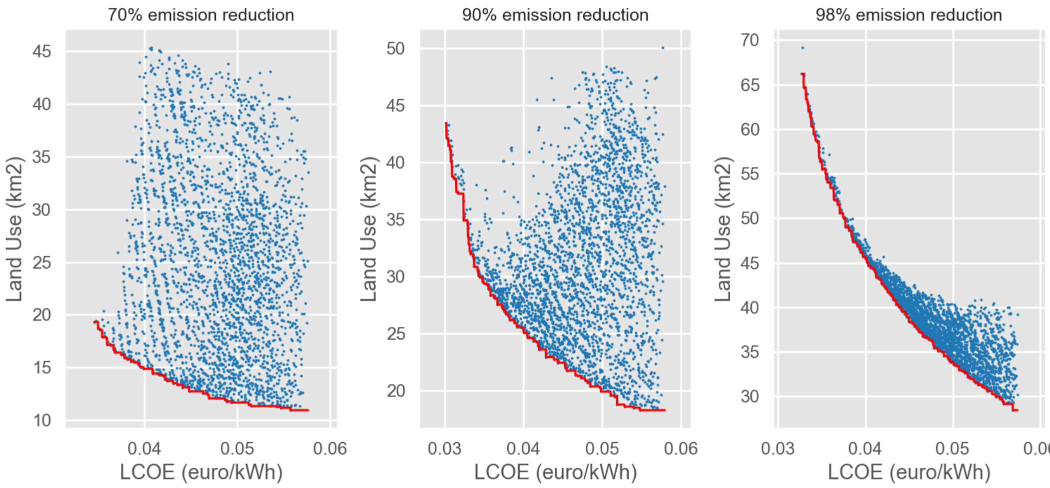


Figure E.7: Evaluating the trade-off between LCOE and land use for different scenario's of CO_2 reduction. The Pareto-front for these specific criteria is shown by a red line.

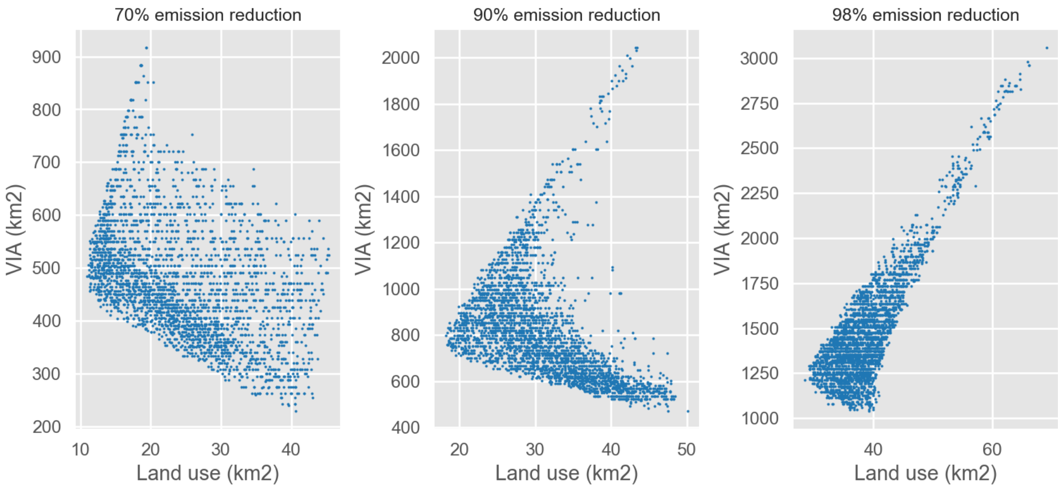


Figure E.8: Evaluating the trade-off between land use and VIA for different scenario's of CO_2 reduction.

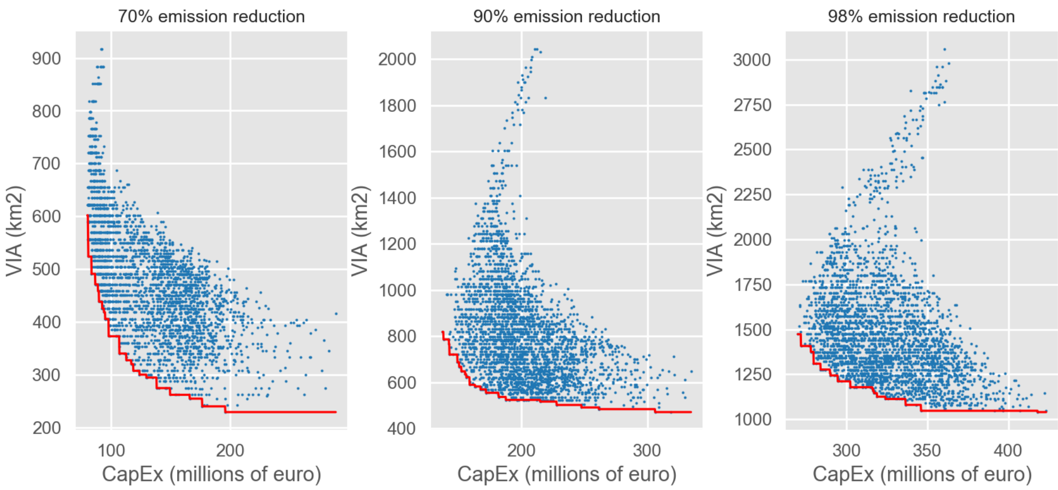


Figure E.9: Evaluating the trade-off between CapEx and VIA for different scenario's of CO_2 reduction. The Pareto-front for these specific criteria is shown by a red line.

F

Analyzing the robustness of the results

The results of this research were obtained using deterministic data: no stochastic data was used. Using deterministic data in an optimization is always a risk. The results of the optimization may be very specifically suited to the exact data that is provided: a local optimum instead of a global optimum is found. In reality, an innumerable amount of uncertainties arise when analyzing a large socio-technical system such as the energy system. This section will evaluate the robustness of the obtained results under differing circumstances: will unexpected changes in the weather or in energy prices influence the performance of the generation mix?

The robustness of the results is verified by changing two aspects of the data input, for which the uncertainty is greatest: the electricity prices and the capacity factors (weather). The electricity prices will be changed to the electricity prices from another year, but from the same source; data from 2017 will be used. For the weather data, no other year is available. Therefore, a random variation of 10% (uniform for each hour) is applied to the data-set, to see how this influences the results. Below, the final results that were found to be the average optimal results for all actors are analyzed for robustness. In appendix F, the total set of outcomes for the second scenario is evaluated for robustness.

F.0.1. Testing the robustness of the final results

The final results are tested for robustness. The results are shown in table F.1. Only the results regarding CO_2 emissions reduction, land use, and LCOE are shown. CapEx and VIA are directly determined by the installed capacities and are not influenced by the change in input data. In can be seen from these results that the obtained results are very robust to the changes applied. LCOE is not influenced by the change in weather. Land use is only slightly higher owing to an increase in biomass use. The reduction in emissions is slightly lower.

The results are similar for the change in price data. The analysis in this section has shown that the optimal average results are not only perfectly suited to the provided data. A random variation in weather or changing the electricity prices still lead to acceptable outcomes. More investigation would be necessary to determine what would happen if changes in energy demand are applied or if generation from RES-E turns out to be systematically lower than expected.

Table F.1: Table showing the results from the robustness test of the final result: the results are robust for variations in the weather and different prices.

	Original			**10% variation in weather**			**Using price data from 2017**		
	LCOE	Land use	Emission reduction	LCOE	Land use	Emission reduction	LCOE	Land use	Emission reduction
Scenario 1	0.041	17	70%	0.041	17	69.50%	0.037	17	70.1%
Scenario 2	0.037	30.8	90%	0.037	31	89.80%	0.036	30.8	90%
Scenario 3	0.041	45.4	98%	0.041	45.6	98%	0.041	45.4	98.05%