Agent-based modelling in energy scenario development

An analysis of contemporary energy scenarios for the Netherlands.

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Preface

This thesis concludes my Complex Systems Engineering and Management degree. Writing this thesis was a challenging, but very rewarding journey. This journey would not have been possible without the support of my supervisors, friends, and family.

Firstly, Emile guided me throughout the process and was always ready to help with trying to understand EMLab. His enthusiasm and patience helped me greatly during times when I was stuck. Secondly, my chair Kornelis Blok provided very constructive criticism from the beginning. He helped me greatly in scoping my thesis and providing a meaningful contribution to the academic debate. Finally, Els van Daalen her comments on my writing and structure helped me greatly and she went beyond the regular responsibilities of a second supervisor in helping me.

My friends, both in the Netherlands and abroad, were crucial in providing support when I was faced with roadblocks in my thesis. I also want to thank my sister and parents, for proofreading my thesis and supporting me unconditionally. Special thanks go out to Rosanna, who supported me, helped with academic writing, and motivated me throughout the whole process.

Executive summary

The Netherlands must reduce its GHG emissions in order to meet international obligations and to combat climate change. This requires a switch from the current Dutch energy mix, which is mainly composed of energy generated from coal and natural gas, to an energy mix dominated by solar and wind energy. In order to determine how the future energy sector of the Netherlands can or should look, energy scenarios are used to explore potential alternative futures. These scenarios can be normative, explorative, and descriptive. Normative scenarios determine a specific future which must be reached and therefore explore the way to realize this future. Explorative scenarios investigate multiple different possible pathways to the future. Descriptive scenarios estimate the future based on the assumption that current business-as-usual is continued. Many scenarios for the Netherlands exist, but a classification of contemporary Dutch electricity scenarios is missing. Additionally, scenarios have to make various assumptions in order to model the energy sector. An example of an assumptions is present in optimisation models, where the model contains the assumption that all information regarding the future is available. Energy investments in optimisation models are therefore fully rational as these investments are optimised for their costs. In practise, energy companies do not know how the future will develop and will therefore in hindsight make non-optimal investments. In order to model how uncertainties influence the behaviour of energy producers, agent-based modelling (ABM) has often been proposed in the literature. However, no research exists on whether agent-based models have been used to develop Dutch energy scenarios and a recent energy scenario suggest that agent-based modelling is not used to develop energy scenarios in the Netherlands.

This research addressed this knowledge gap through the following research question: “To what extent is agent-based modelling currently used in Dutch energy scenarios and how can it benefit the future development of scenarios?”. To answer this, the research first dissects Dutch energy scenarios for 2030 which are focused on the electricity sector. Second, it analysed specific Dutch energy scenarios with the Energy Modelling Laboratory (EMLab), an agent-based model. Seven scenarios were classified, and two scenarios were analysed with EMLab. The scenarios that were analysed are the Nationale Energie Verkenning and the calculations of the recent Dutch climate agreement. The main goal of this research is to explore whether ABM is used to develop scenarios, while also exploring how ABM can benefit scenario development. Thereby, it does not aim to propose ABM as a substitute for current models used in scenario

development, but rather how ABM can complement current models and provide additional insights. The results of ABM thus coexist next to the estimates of the scenarios.

To explore how ABM can benefit scenario development, EMLab was used to analyse two scenarios. Firstly, the inputs that were used for the scenarios were also used for the agent-based model. Secondly, the scenario estimates for 2030 were compared to the agent-based model results for 2030. These estimates were the installed capacity in 2030, the electricity prices in 2030, and the electricity production in 2030. The differences in the results between both approaches were linked to agent behaviour and the role uncertain information can play. A schematic overview of the research approach can be seen in figure 1.

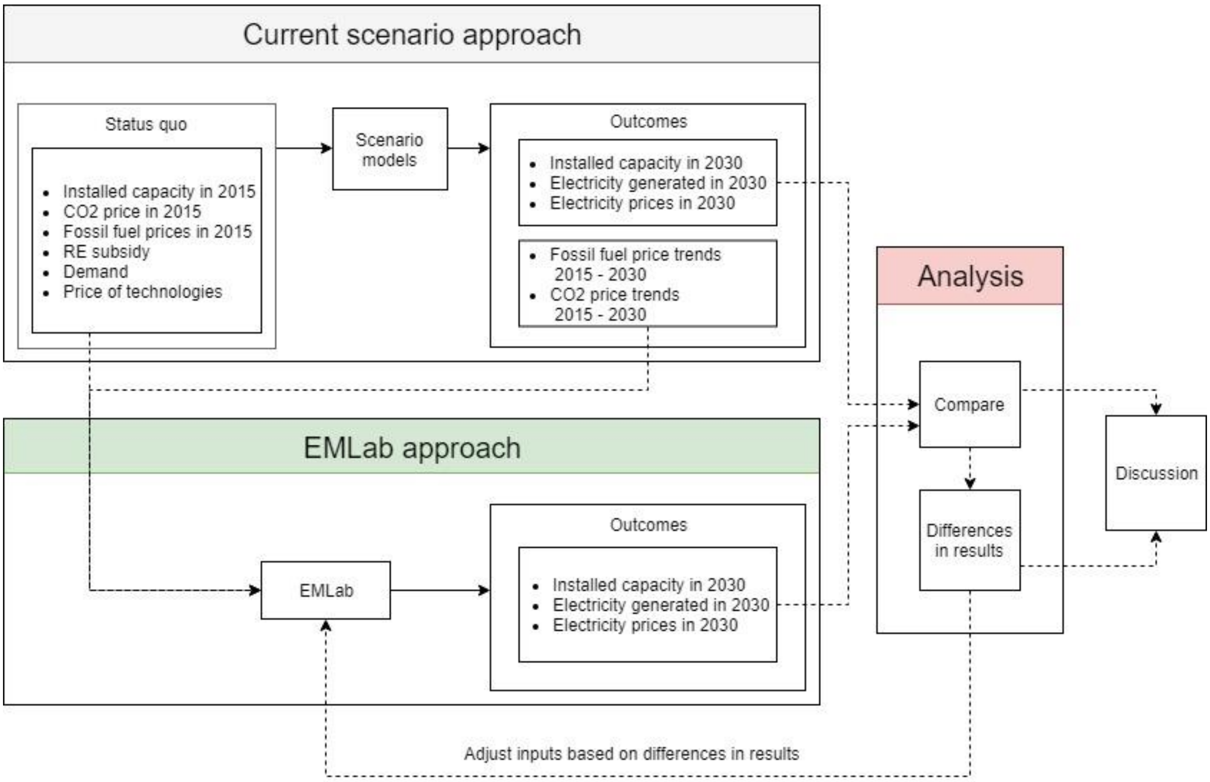

Figure 1. A schematic overview of the methodology.

The dissection of the scenarios showed that agent-based models are currently not used to develop energy scenarios for the Netherlands. All scenarios mention the importance of behaviour and how it is an uncertainty for the future. However, none of the dissected scenarios model behaviour through an agent-based model. Most scenarios used optimisation models which assumed that energy companies have perfect information for the future. All investments in these scenarios were therefore optimal and overinvestments were not mentioned in the scenarios. The goal of the scenarios was either to forecast the future based on the current policies and planned investments, to determine how a fully renewable energy sector could look like, or what impact specific climate policies will have on the energy sector.

The ABM results showed that initially the estimates of both scenarios could not be obtained with EMLab when the same inputs and current renewable subsidies were used. This was caused by the fact that the energy companies in EMLab conducted more investments in natural gas than they do in the scenarios. The reason for this is likely that many existing Dutch natural gas power plants will be decommissioned between 2015 and 2030 due to them reaching their end-of-life. Combined with an increase in electricity demand or a constant electricity demand as estimated by the scenarios, this leads to energy producers investing in natural gas power plants as found in the EMLab analysis. The energy producers in EMLab assume that the lack of generation capacity in the future will cause electricity prices to increase greatly. Therefore, they invest in order to benefit from this lack of supply. Specifically, investments in Open-Cycle Gas Turbines (OCGT) were conducted in EMLab and the increase in renewable installed capacity as estimated by the scenarios is unable to prevent these natural gas investments. However, investments into OCGT did not appear profitable in the time analysed in this research, as almost no electricity was produced by OCGT power plants. Furthermore, no electricity shortages occurred in which these plants could recover their costs.

When natural gas investments were prohibited or limited, the EMLab results were similar to the scenario estimates. This showed that the impact of behaviour can be limited by specific policy interventions. However, these policy interventions can have unintended consequences as the results showed that when the demand increased more than expected, the interventions caused large electricity shortages to occur. Generally, the analysis of both scenarios showed that the Dutch natural gas capacity in 2030 will be higher than estimated in contemporary scenarios when uncertain behaviour is included. This ABM analysis has shown that certain market signals, such as a decreasing available supply of reliable generation technologies, could incentivize energy producers to invest beyond what appears financially recoverable in the long run. The ability of ABM to both reach the same estimates as current scenarios, while also providing additional insights in what behaviour might emerge shows how ABM can provide new insights which do not arise when optimisation models are used. The recommendation is therefore to include ABM for scenario developing. Future research could look at the specific time-requirement and costs of incorporating ABM in scenario development.

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List of abbreviations

ABM	Agent-based modelling
BAU	Business as usual
CBS	Centraal Bureau voor de Statistiek
CCGT	Closed Cycle Gas Turbines
CGE	Computable general equilibrium
CPB	Centraal Plan Bureau
DLR	Deutsches Zentrum für Luft- und Raumfahrt
ECN	Energieonderzoek Centrum Nederland
EMLab	Energy Modelling Laboratory TU Delft
ER	Energy [R]evolution
ETM	Energy Transition Model
GDP	Gross domestic product
GHG	Greenhouse gas
GW	Gigawatt
IEA	International Energy Agency
KA	Klimaatakkoord
KA-act	Klimaatakkoord actuele prijzen
KWh	Kilowatt hour
MWh	Megawatt hour
NDE	Nederland 100% Duurzame energie in 2030
NEV	Nationale energie verkenning
OCGT	Open Cycle Gas Turbines
PBL	Planbureau voor de Leefomgeving
PJ	Petajoule
SDE+	Stimulering Duurzame Energieproductie
SOE	Scenario-ontwikkeling energievoorziening
VE	Verkenning energievoorziening 2035
VOLL	Value of Last Load
WEO	World Energy Outlook
WLO	Welvaart en Leefomgeving

1. Introduction

The Dutch electricity sector will have to drastically reduce its carbon emissions in order to meet the targets in the Paris Agreement (Regeerakkoord, 2017). The Paris Agreement is an international agreement that incentivises countries to limit the global average temperature increase to 2 degrees Celsius above pre-industrial levels (Rogelj et al., 2016; Streck, Keenlyside, & von Unger, 2016). In order to stay below this limit, each country must reduce its greenhouse gas (GHG) emissions by a certain percentage. The main driver of the Paris Agreement is that GHG induced climate change can have a drastic effect on the environment, the economy, and on human lives (Rogelj et al., 2016; Streck et al., 2016). Examples of options to limit GHG emissions that the Dutch government is pursuing are to close existing coal power plants, construct several wind farms, and promote solar photovoltaic (PV) systems in order to reduce these emissions (Kamiński & Saługa, 2018; Regeerakkoord, 2017). Despite these efforts, the Netherlands is currently one of the European countries with the lowest share of renewables (Eurostat, 2017). As a result, the aim of the Dutch government is to facilitate the instalment of a large amount of additional solar and wind capacity (Regeerakkoord, 2017). Until 2023, at least 4.5 GW offshore wind energy is planned by the Dutch government, with an additional 7 GW planned between 2023 and 2030 (Rijksdienst voor Ondernemend Nederland, 2019). In addition to this combined 11.5 GW installed wind power capacity, the government is subsidising solar energy (Regeerakkoord, 2017). However, it is unclear how much capacity should be installed in order to meet the Paris Agreement. Recently, the Planbureau voor de Leefomgeving (PBL) published that the measures set forward in the Dutch climate agreement were insufficient to reach these targets (Van Hout, Koutstaal, & Özdemir, 2019).

The energy sector is a complex system with a variety of actors, societal and technological components (Bale, Varga, & Foxon, 2015; Nakicenovic, 2000). Additionally, monopolistic properties and large infrastructural sunk costs are part of the system (Buhanist, 2015). Transmission lines, pipelines, and power plants require great initial investments and rely on their long lifetime in order to recover the initial costs. Sunk costs play a crucial role in the decision-making of energy companies when determining how much they should invest exactly (Buhanist, 2015). An example of large sunk costs is the initial instalment price of gas pipelines, where 70% to 80% of the total costs are constituted by material and labour costs (Rui, Metz, Reynolds, Chen, & Zhou, 2011). These large sunk costs are problematic in case of overcapacity, as this leads to substantial financial losses because the marginal costs are not enough to cover the capital costs. On the other hand, under capacity misses out on revenue, because of an inability to meet demand and can lead to great societal impacts due to a lack of security of supply (Lijesen, 2007). Furthermore, if power plants must be closed due to new laws, companies either must be compensated financially or face large losses due to these unrecoverable costs (Buhanist, 2015; Kamiński & Saługa, 2018).

Secondly, the demand for electricity is very inelastic (Lijesen, 2007). This is because there is a continuous basic need for energy. As a result, if there is a shortage on the electricity market, electricity prices can increase greatly due to the fact that the willingness to pay is very high (Lijesen, 2007). When not enough electricity is supplied to meet demand, prices can reach the Value of Lost Load (VOLL). The VOLL is the maximum price consumers are willing to pay for electricity (Tol, 2007). For the Netherlands, the VOLL can be several thousands of euros per MWh (Mulder, 2017). However, on the other hand if more electricity is produced than needed for demand, consumers are not willing to buy this electricity (Lijesen, 2007).

As solar and wind power produce electricity much more intermittent than traditional fossil fuels, due to their dependency on weather conditions, these price fluctuations become more significant and therefore more disrupting (Gowrisankaran, Reynolds, & Samano, 2011). Therefore, measures will have to be found to mitigate this intermittence. Options to mitigate this intermittence could be to install flexible fossil fuel generators, such as Open Cycle Gas Turbines (OCGT) with low capital costs and high marginal costs (Lijesen, 2007). Another option could be storage, although this would most likely only be a solution for short duration shortages (Gowrisankaran et al., 2011). Finally, increasing the interconnectivity with neighbouring countries could help to reduce the effects of intermittency (Brouwer, van den Broek, Zappa, Turkenburg, & Faaij, 2016). However, all these options require large capital investments and take several years before they become operational (Kamiński & Saługa, 2018). This construction time, combined with the great upfront costs, reduces the willingness of companies and transmission system operators to invest in these solutions, as they require certainty and stability before investing.

One way to determine how much installed capacity should exist in order to comply with, for example, the Paris Agreement, is by using scenarios (Paltsev, 2017). Scenarios are constructed in order to explore possible futures (Peterson, Cumming, & Carpenter, 2003; Schoemaker, 1995). Energy scenarios explore how the energy sector might develop in the future, partially by determining how policies or external influences can shape the sector. Recent

Dutch scenarios are, for example, exploring what measures should be taken in order to reduce CO_2 emissions. Scenarios can have different aims and purposes, as they can be predictive, explorative, or normative (Peterson et al., 2003; Van Notten, Rotmans, van Asselt, & Rothman, 2003). At the core of all scenarios are energy models (Lund et al., 2017; Weijermars, Taylor, Bahn, Das, & Wei, 2012). Energy models are used to determine how the sector will change over time. However, models are only a representation of reality and many assumptions are made in order to represent reality in models (Chappin, 2011).

In order to determine how accurate energy scenarios have been historically, many scholars have looked at the validity of scenarios. For example, Bezdek and Wendling (2002) conducted an analysis of energy predictions for the United States between 1952 and 2001. They found that scenarios which assume a drastic change in people's behaviour were most often incorrect. Another issue that they identified is that scenarios almost always underestimated the role and impact of the market (Bezdek & Wendling, 2002).

As already mentioned the behaviour of actors is very important but difficult to model (Bezdek & Wendling, 2002; Kraan, Kramer, & Nikolic, 2018). Assumptions must be made in order to try to understand this behaviour. Classic optimization models, for example, assume that one actor has perfect information available to them (Pfenninger, Hawkes, & Keirstead, 2014). Perfect information implies that the actor knows how the future will develop and that their decisions are fully rational and based on this information (Pfenninger et al., 2014). However, as stated in the literature and in the recent calculations of the Dutch climate agreement, actors do not operate under perfect information and might not operate fully rationally (Chappin, 2011; Pfenninger et al., 2014; Van Hout et al., 2019).

A method to simulate this non-rational behaviour is agent-based modelling (ABM) (Chappin, 2011; Dam, Nikolic, & Lukszo, 2013; Farmer & Foley, 2009; Hansen, Liu, & Morrison, 2019). In ABM, actors can be represented as agents in a specific environment (Dam et al., 2013). The environment and the agents can be shaped by the modeller in order to create a representation of a complex system. In ABM, agents can be created who have limited knowledge of the future (Richstein, Chappin, & de Vries, 2014). These agents base their decisions on the actions of other agents and on how the information that is available to them. Because this technique can simulate how energy companies might act, it has often been advocated for scenario developing for complex systems such as the energy sector (Chappin & Dijkema, 2008; Farmer & Foley, 2009; Van Notten et al., 2003).

Although the benefits of ABM for scenarios have been brought up since 2003, little research exists on whether they have been used for contemporary Dutch energy scenarios (Van Notten et al., 2003). Additionally, the concrete difference between an ABM approach and current scenario approaches have not been highlighted. To address this knowledge gap, this research will address the following question:

To what extent is agent-based modelling currently used in Dutch energy scenarios and how can it benefit the future development of scenarios?

Firstly, this thesis will classify Dutch energy scenarios based on aspects as defined in the literature. This will be done in order to obtain an overview of the scenarios with the aim of gaining insight into what extent ABM or properties of ABM are used. Secondly, it will investigate if an agent-based model reaches the same estimates for 2030 as the scenarios do when inputs for both approaches are the same. If the outcomes are not the same, the inputs for the agent-based model will be adjusted in order to reach the outcomes of the scenarios. Finally, the adjustments that had to be made in order to calibrate both results will be discussed and connected to the agent-based properties of ABM. Energy scenarios can contain information for heat, transport, and the electricity sector. This research will focus on the electricity sector in particular.

The main goal of this research is to explore how ABM can benefit scenario development. Thereby, it does not aim to propose ABM as a substitute for current models used in scenario development, but rather how ABM can complement current models and provide additional insights. The results of ABM should thus coexist next to the estimates of the scenarios. The goal is, by mirroring the scenario estimates, to determine what impact agent behaviour has.

1.2 Research questions

In order to answer the main research question, the following sub-questions are derived.

1. How can current energy scenarios for the Netherlands be classified?
2. How do results of an ABM approach differ compared to the outcomes of recent Dutch energy scenarios?
3. What new insights can an ABM approach provide for scenario development and what does this mean for the contemporary scenarios?

Sub-question 1 will analyse contemporary energy scenarios for the Netherlands according to characteristics of scenarios as defined in the literature. Sub-question 2 will identify how the installed capacity, electricity prices, and electricity production in 2030 differ for the scenarios compared to an ABM analysis with one specific model. For this analysis, two different types of scenarios will be selected based on the classification. Sub-question 3 links differences in the results between the scenarios and the ABM analysis to the properties of each modelling method. It will also answer how ABM can benefit scenario development.

1.3 Theoretical and practical relevance

This research will be relevant for anyone who works with energy scenarios. A classification of current energy scenarios may support energy companies as well as policy makers in understanding all the different scenarios that exist and what differences there are between these scenarios. Furthermore, the last years the Dutch energy sector has seen an overcapacity of installed generation due to construction of new coal power plants (Van Dril, 2017). Additionally, since coal power plants will be closed by Dutch government in 2030, these investments are even less usable in hindsight. Overcapacity would not exist if actors have perfect foresight for the future, but in reality, actors do not have perfect information. The current existence of overcapacity in the Dutch energy market therefore shows how important it is to understand how uncertain behaviour might influence the energy sector in the future in order to both prepare for the effects of uncertain behaviour and to mitigate its consequences. The findings of this research will give an insight in whether agent-based models are currently used for the development of energy scenarios for the Netherlands for 2030. Additionally, it will show how ABM can improve scenarios and how the behaviour of energy companies might influence the energy sector.

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2. Theoretical background

Scenarios for the energy sector became prominent around 1960-1970 due to growing international uncertainties and events such as the oil crisis of 1973-1974 (Jefferson & Voudouris, 2011; Weijermars et al., 2012). During these decades, a wide range of literature has been written on the topic. This section will firstly determine what classifies as a scenario and what definitions have been given to the concept. Secondly, it will explore methods used to distinguish between different types of scenarios. Thirdly, it will address commonly used modelling techniques for electricity scenarios, such as top-down, bottom-up, narrative, and agent-based modelling techniques. Finally, it will investigate which properties are relevant in analysing/classifying energy scenarios.

2.1 Literature review

2.1.1 What is a scenario?

As defined by Peterson et al. (2003), scenario planning is a systemic method to explore the possible futures. They define the core of scenario planning as determining how the uncertainties present in a complex system can shape different futures. Peterson et al. (2003) further specify that scenarios cannot accurately predict the future, and that they should not be forecasts due to the structural uncertainties of systems. Alternatively, Schoemaker (1995) defines scenario planning as attempting to use a large amount of data to present possible narratives for the future. Millet (2003) highlights the fact that there are multiple different definitions of scenarios, and that this conflicting terminology hinders the usefulness of scenarios. Building onto the work of Millet, Bradfield et al. (2005) conclude that the definitions of planning, thinking, forecasting, analysis, and learning are core concepts in scenario planning, but that various interpretations exist on the role of these concepts in scenario planning and on their specific meaning (Bradfield, Wright, Burt, Cairns, & Van Der Heijden, 2005). An example of this conflicting terminology can be seen in Peterson et al. (2003) and Wilkinson (2009) which state that scenarios should not be called predictions or forecasts. In contrast, Börjeson et al. (2006) and Van Notten et al. (2003) do use the terms ‘prediction’ and ‘forecast’ to describe scenarios.

Influential actors in the energy sector and in scenario development seem to avoid intermingling scenarios with forecasts. For example, Shell defines scenarios as “not projections, predictions, or preferences; rather, they are coherent and credible alternative stories about the future.” (Cornelius, Van de Putte, & Romani, 2005, p. 93). The International

Energy Agency (IEA) defines scenarios as "not forecasts for the future, but a way of exploring different possible futures, the levers that could bring them about, and the interactions that arise across a complex energy system." (World Energy Outlook, 2018, p. 1). The World Energy Council (2013) defines scenarios as "alternative views of the future which can be used to explore the implications of different sets of assumptions and to determine the degree of robustness and possible future developments" (Gadonneix et al., 2013, p. 1). The reluctance of these organizations to define scenarios as forecasts, while influential literature from the early 2000s does sometimes define scenarios as forecasts shows that Millet's (2003) point regarding the conflicting terminology in scenarios is either still present, or that in the present scenarios are no longer defined as forecasts. In order to stay clear of the discussion regarding the conflicting terminology, scenario results in this research will be called estimates.

2.1.2 Different classifications

Despite the ongoing discussion on the definition of scenarios, all scenarios contain assumptions in order to deal with uncertainties. Examples of uncertainties are the future electricity demand, the behaviour of actors in the sector, and on how high fossil fuel and CO_2 prices will be in the future (Börjeson et al., 2006; Van Notten et al., 2003). In addition to these general characteristics, a distinction between different types of scenarios can be made based on other factors. Börjeson et al. (2006) conducted a literature review on different types of scenarios and concluded that although many specific types can be distinguished, in general these types can be classified as either predictive, explorative, or normative scenarios. Where predictive scenarios explore "*What will happen?*" explorative scenarios try to identify *"What can or could happen?"* and normative scenarios determine "*How could a specific future be reached?*"(Börjeson et al., 2006). Van Notten et al. (2003) and Nakicenovic (2000) classify scenarios as either descriptive or normative, where descriptive scenarios explore open-ended paths into the future. Normative scenarios are value-based and explore options to reach a desirable future (Nakicenovic, 2000; van Notten et al., 2003).

One of the mostly used typologies of scenarios is created by Van Notten et al. (2003). Van Notten et al. (2003) created a scenario typology after conducting an extensive literature review. Their typology classifies scenarios according to three themes: the project goal of the scenario, the process design, and the content. To classify the main goal of the scenario they state that scenarios can be either normative or descriptive. Normative scenarios describe what should be done in order to reach a desired future, while descriptive scenarios explore the possible futures. They found that most scenarios at the time of their research were descriptive. Related to this, they make a distinction between scenarios that use backcasting techniques, which explore what needs to be done to reach a specific future and thereby are normative and the other hand, forecasting scenarios, which are explorative and therefore descriptive by nature. Furthermore, Van Notten et al. (2003) state that a classification can be made based on the subject of the scenario, the time scale, and its spatial scale.

For the process design, Van Notten et al. (2003) define two groups of scenarios based on the type of tools that they use, namely qualitative and quantitative scenarios. Qualitative scenarios contain high levels of uncertainty and narrative elements, while quantitative scenarios contain large amount of technological detail. Vuuren (2007) also uses if a scenario uses qualitative or qualitative tools to distinguish between scenarios. Additionally, for process design Van Notten et al. (2003) further differentiate between method of data collection, resources, and institutional conditions. Finally, for the scenario contents they differentiate based on the temporal nature, the nature of the variable (i.e. the number of variables explored), the nature of the dynamics, the level of deviation, and the level of integration. The level of deviation differs for scenarios since some scenarios contain a business-as-usual element which determine how the sector will look like when the current status-quo is continued. The other group are scenarios which contain many unconventional disruptions. The level of integration looks at how inter-connected the sectors in a scenario are (Van Notten et al., 2003). Since most of these components are relevant in order to classify scenarios, a table was constructed which contains the most relevant components. This table will be used to support the dissection of the scenarios

Van Vuuren (2007) highlights that the method that scenarios use to deal with uncertainties is used to make a distinction between scenarios. Firstly, scenarios can contain multiple pathways which use different values of the uncertainties in these pathways. Secondly, scenarios can be fully probabilistic, where a probability density function is used in order to mitigate uncertainties. Van Vuuren (2007) and Keles (2013) state that fossil fuel prices, CO_2 prices, energy demand, innovation, and policies are important uncertainties in electricity scenarios (Keles, 2013; Vuuren, 2007). Based on the literature review, the main classification that is used to describe scenarios is whether they are predictive, explorative or descriptive, and normative and the Dutch energy scenarios will be grouped based on these definitions.

Furthermore, the other characteristics that were found in this literature review will also be used to provide an overview and can be seen in table 1.

Table 1. Overview of characteristics as found in the literature.

Component	Options	Explanation	Source
General type	Predictive	Determines what will happen	(Börjeson et al., 2006)
	Explorative	Determines what can happen	(Börjeson et al., 2006; Van Vuuren 2007)
	Descriptive	Explores the possible futures	(Nakicenovic, 2000; Van Notten et al., 2003)
	Normative	Determines what should happen	(Börjeson et al., 2006; Nakicenovic, 2000; Van Notten et al., 2003; Van Vuuren 2007)
Methods	Backcasting	What needs to be done to reach a specific future	(Van Notten et al., 2003)
	Forecasting	Explore the future	(Van Notten et al., 2003)
	Other methods	Own perception	
Subject	The main subject of the scenario		(Van Notten et al., 2003)
Timescale	The time that is analysed		(Van Notten et al., 2003)
Spatial	Supranational/National/Local		(Van Notten et al., 2003)
Data	Qualitative	High level of uncertainty	(Peterson et al., 2003; Van Notten et al., 2003; Van Vuuren, 2007)
	Quantitative	Large amounts of technical detail	(Peterson et al., 2003; Van Notten et al., 2003; Van Vuuren, 2007)
Level of deviation	Business as Usual (BAU)		(Van Notten et al., 2003)
	Unconventional disruptions		(Van Notten et al., 2003)
Uncertainties:			
Method	Alternative scenario approach	Uncertainties are captured by different scenario storylines	(Van Vuuren, 2007)
	Probabilistic approach	Probability density functions for parameters	(Van Vuuren, 2007)
Fossil fuel prices	Fossil fuel prices		(Keles, 2013; Van Vuuren, 2007)
CO_2 *prices*	CO_2 prices		(Keles, 2013)
Energy Demand	Demand		(Keles, 2013; Van Vuuren, 2007)
Innovation	Innovation		(Keles, 2013; Van Vuuren, 2007)
Policies	Policies		

2.2 Modelling of scenarios

Energy scenarios rely largely on models in order to identify their results. Energy models were classified in two general categories: bottom-up models and top-down models (Hourcade et al., 1996; Van Beeck, 1999). Although there are some conflicting definitions regarding the terms, bottom-up models usually contain a large amount of technical details and predict the future without looking at other sectors influencing the energy sector. Top-down models look at the energy sector from a more economic perspective, by including welfare and profit maximization, without looking at the technical details (Beckman, Hertel, & Tyner, 2011; Böhringer, 1998; McFarland, Reilly, & Herzog, 2002). Bottom-up modelling requires large amounts of data and looks at energy sectors from a disaggregated level (Kavgic et al., 2010). Due to their disaggregation, bottom-up models are usually unable to incorporate macroeconomic dynamics or policies. Bottom-up modelling is often considered an engineering approach, while top-down is considered a macro-economic approach (Hourcade et al., 1996; Ruijven, 2008). Hourcade et al. (1996) identify two main groups in bottom-up modelling; descriptive and prescriptive models. Descriptive models in general are argued to focus on predicting, while prescriptive models are aiming to explore what is possible (Van Beeck, 1999). Common bottom-up techniques are optimisation models, simulation models, and multi-agent models (Helgesen, 2013; Herbst, Toro, Reitze, & Jochem, 2012; Jacobsen, 1998; Ruijven, 2008).

Many top-down models do not look at the energy sector alone but consider the interactions with other sections of the economy. Furthermore, they look at the energy sector from an aggregated perspective (Van Beeck, 1999). Common top down approaches are input-output models, econometrics models, computable generable equilibrium (CGE) models, and system dynamics models (Helgesen, 2013). Historically, the earliest energy scenarios used top-down modelling. One important conclusion that Van Beeck (1999) found is that although specific types of models are usually associated with either the top-down category or the bottom-up category, in reality many models contain aspects of both definitions. For example, optimisation models are usually classified as bottom-up models. However, economic top-down models have started to include optimisation as well. In general, the following distinction can be made between the two types as seen in the table 2.

Table 2. An overview of the characteristics of top-down and bottom-up models.

Type	Top-down models	Bottom-up models	Source
Data	Aggregated data	Disaggregated data	Paltsev, 2017;
Perspective	Economic perspective	Technological perspective	Helgesen, 2013; Paltsev, 2017; Van Beeck, 1999
Market interaction	Influenced by the market	Independent of market	Hourcade et al., 1996; Van Beeck, 1999
Sectors	Inter-sectoral connections	Stand-alone sector	Paltsev, 2017
Technological innovations	Disregards technological innovations	Focus on technological properties	Hourcade et al., 1996; Helgesen 2013; Ruijven
Macro-economic factors	Considers macro-economic feedbacks	No focus on macro-economic influences	Ruijven; Hourcade et al., 1996;
Micro-economic factors	Considers micro-economic decision-making	No focus on micro-economic decision-making	Ruijven; Hourcade et al., 1996
Policies	Focus on policies, but is unable to combine policies with technology	No interaction between policies and the model	Hourcade et al., 1996
Examples	CGE, Input-Output, econometrics, and system dynamics models	Optimisation, simulation, and multi-actor models	Helgesen, 2013; Paltsev, 2017, Van Beeck, 1999

A narrower distinction can be made for energy scenario models. Lund et al. defined two archetypes for energy scenario modelling, optimisation and simulation models (Lund et al., 2017; Pfenninger et al., 2014).

2.2.1 Optimisation models

Optimisation models are currently often used to model the energy sector (Ma & Nakamori, 2009; Pfenninger et al., 2014; Weijermars et al., 2012; Zeng, Cai, Huang, & Dai, 2011) . At the core of optimisation models is an objective function for which an optimal solution is found (Hobbs, 1995; Ma and Nakamori, 2009). In addition optimisation models can contain many constraints, rules, and assumptions (Lund et al., 2017; Ma & Nakamori, 2009). The interpretation of these depends on the modeller (Hobbs, 1995). Classic optimisation models often use a central entity who has perfect information and foresight on future changes in the system (Pfenninger et al., 2014). For the energy sector, the goal of optimisation is often to find “the most effective method of production”(Matliare, 2012, p. 2). This most effective method can be linked to the cheapest fuel mix for a country (Weijermans, 2012). Constraints for this fuel mix could be for example reliability and amount of GHG emissions.

2.2.2 Simulation models

The main difference between optimisation and simulation models according to Lund et al. (2017) is that optimisation models aim to find the optimal solution, whereas simulation models want to explore how a system will act in the future. Related to this is that Edmons (2017) states that in order to understand optimisation models, one can analyse the mathematics behind it. For simulation models this is harder because the goal of simulation models is to determine how a system will work (Edmonds, 2017). Additionally, optimisation models define risks quantitatively while simulation models use more qualitative methods (Lund et al., 2017). However, this does not mean that simulation models do not contain a solid mathematical foundation and basis (Fleiter et al., 2018). Rather, the goal of simulation modelling is not to find the mathematical optimum, but to find how mathematical relations might develop. A relatively new type of simulation models are agent-based models (Macal & North, 2010).

2.2.3 Agent-based models

Macal and North (2010) state that typical agent-based models contain agents, interactions between these agents, and an environment. Furthermore, they state that the most important property of ABM is that agents act autonomously and are not guided (Macal & North, 2010). The main benefits of ABM are that agent-based models shows emergent behaviour, that they can display a natural description of systems, that they are flexible, and that they are cost effective (Bonabeau, 2002; Bazghandi, 2012). Emergent behaviour is the collective behaviour that occurs by the interactions of individual agents. An example of emergent behaviour could be the presence of overcapacity in the Dutch electricity market because of the individual investment behaviour of agents. A natural description of the system related to the fact that reality can be displayed more naturally than other modelling techniques can. An example is provided by Bonabeau who states that “it is more natural to describe how shoppers move in a supermarket than to come up with the equations that govern the dynamics of the density of the shoppers (Bonabeau, 2002, p. 7281). Agent-based models are flexible as easily more agents can be added to a model or the properties of the agents can be changed. Bzaghandi explains that ABM is cost-effective and a timesaving approach but does not explain why it is so.

Contrary to classic optimisation models as defined by Pfenninger et al., one of the main differences between ABM and optimisation models for the energy sector is that in traditional optimisation models, investments are made by a central planner who has perfect information (Pfenninger et al., 2014). In an agent-based model, the lack of perfect information and the autonomy of agents will therefore most likely lead to sub-optimal investments compared to the outcomes of an optimisation model. Ma and Nakamori (2009) directly compared ABM to traditional optimisation models and concluded that each specific modelling technique has its own purpose, stating that optimisation models are focussed on determining 'what should be' thus what the best option is for decision makers from a financial point of view. Alternatively, ABM looks at 'what could be' in a sense that it shows how different actors could react in different scenarios. Hansen et al. (2019) conducted a literature review on the applications of agent-based modelling in energy transitions. They found that ABM of energy transitions is becoming more popular due to a focus on the complexity of the energy sector. The increasing popularity of ABM is often mentioned in the literature.

As mentioned previously the most defining feature of ABM is the behaviour of the agents. Optimisation modelling also contains behaviour, but certain assumptions are made for this behaviour. Optimisation models assume that one central agent behaves perfectly rational and has full information (Pfenninger et al., 2014). The recent calculations of the climate agreement by PBL have also stressed that their model contains an actor which behaves perfectly rational, while in reality actors might not be and might be risk averse (Van Hout et al., 2019).

3. Methodology

The following paragraphs first explain which research design was chosen and why it is appropriate to answer the research questions posed in this study. Second, the approach to data collection is outlined. Third, it is explained how the agent-based analysis was conducted and how the results were obtained.

3.1 Research design

The research design used in this study is twofold. Firstly, the scenarios were dissected and qualitatively analysed in order to enable classification, determine whether behavioural properties are present, and obtain the inputs and assumptions that were used in the scenarios. Secondly, these inputs and assumptions were used in an agent-based model in order to analyse the scenarios in combination with an ABM. Examples of these inputs are the installed capacity in the reference year, the electricity demand, and the costs of installing additional capacity. A schematic overview of this can be seen in figure 2.

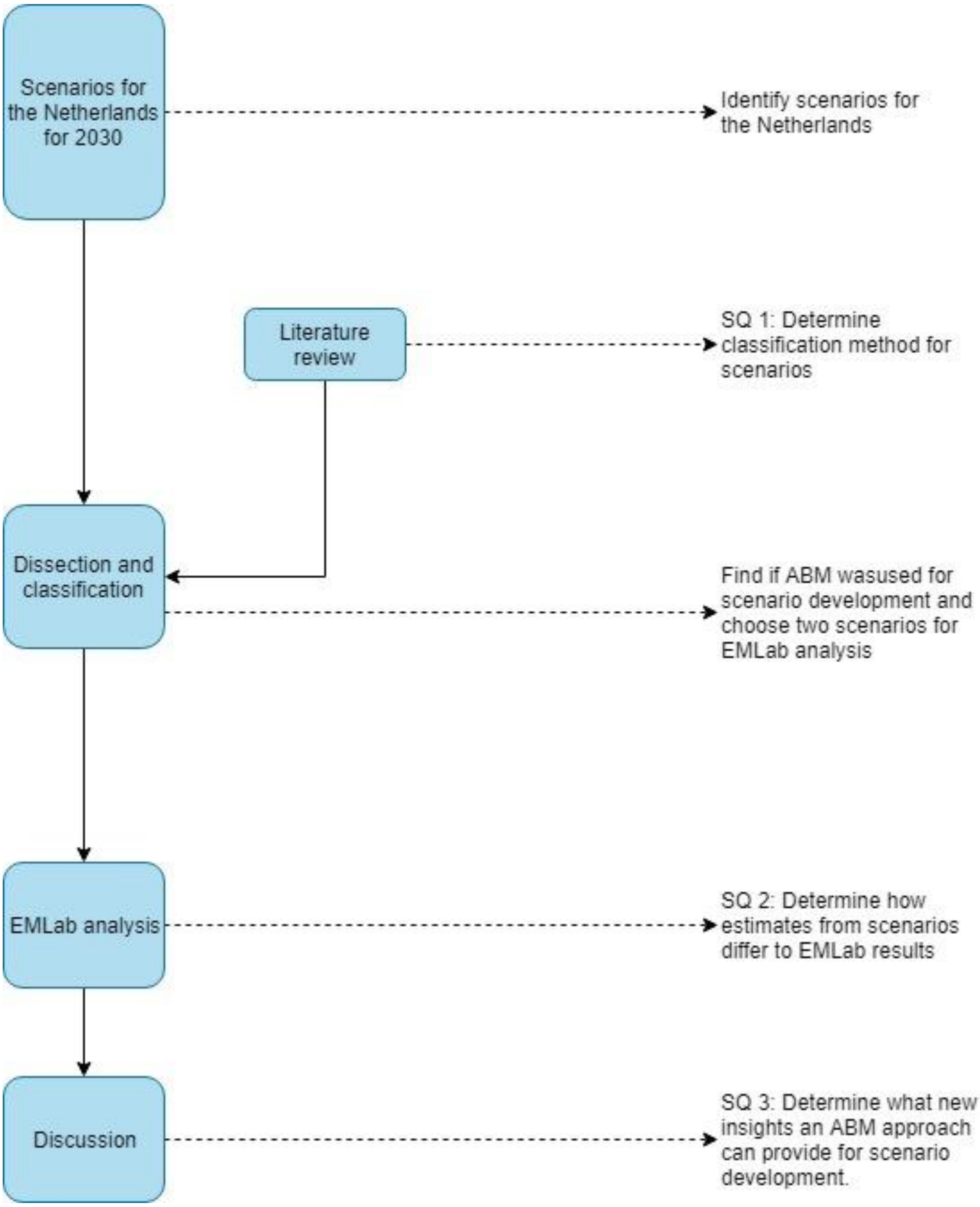

Figure 2. Overview of research design

3.1.1 Classification

The specific characteristics of a scenario are usually not outlined explicitly in the scenarios. Therefore, they had to be found by looking at the scenario's method of analysis, their incorporation of assumptions, their aim, and their modelling of behaviour. A classification in this manner is necessary in order to be able to categorize the different Dutch energy scenarios.

In addition, this categorization enabled a comparison between the different categories rather than a comparison of all scenarios individually.

3.1.2 ABM analysis

After the classification, the two most relevant scenarios were chosen and analysed with an ABM. Through this way, the research investigated whether the use of an ABM changes the outputs of the scenarios in comparison to not using an ABM. This design helps exploring whether behaviour is a crucial variable in determining outcomes, as well as whether current energy scenarios would be different if an ABM was used.

3.2 Data collection

To find relevant electricity scenarios for the Netherlands, an online search was conducted which looked at news articles, journal publication, and the websites of energy actors. Additionally, a publication made by Berenschot for the Dutch Ministry of Economic Affairs and Climate which conducted a literature review on existing Dutch scenarios was used to verify the selected scenarios (Den Ouden, Lintmeijer, Bianchi, & Warnaars, 2018). Five keywords were used, both in Dutch and in English: Dutch, energy, scenarios, 2030, and electricity. To expand the search, different combinations of these keywords were used in multiple search queries.

Several scope decisions were taken. Firstly, scenarios for Europe which contain only a small section regarding the Netherlands were excluded in the analysis. Secondly, scenarios also had to contain enough detail of the electricity sector in order to make sure they could be analysed with ABM. Thirdly, the scenarios had to contain detailed data for 2030. Therefore, scenarios which had a final year which was not 2030 could still be used, if they contained enough data for 2030. Finally, the scenarios had to have the whole of the Netherlands as their scope and primarily include on the electricity sector.

The selected scenarios are displayed in the table 3. In total, nine scenarios were found. However, three scenarios were excluded because one by Tennet did not contain enough information regarding the electricity sector and installed capacity for the, while the others by Natuur&Milieu and Gasunieverkenning did not contain details for 2030 specifically.

Table 3. Overview of the scenarios.

Scenario name	Abbreviation	Date of publication	Included
Nationale Energie Verkenning	NEV	October 2017	Yes
Scenario-ontwikkeling energievoorziening 2030	SOE	June 2014	Yes
Energy [r]evolution	ER	May 2013	Yes
Nederland 100% Duurzame energie in 2030	NDE	March 2014	Yes
Verkenning energievoorziening 2035	VE	July 2017	Yes
Calculations of Klimaatakkoord	OKA	May 2019	Yes
Natuur&Milieu		June 2016	No
Gasverkenning		May 2016	No

3.3 Analysis

3.3.1 Classification

In order to accurately present the scenarios in this research, each scenario was investigated through three steps. First, for each scenario uncertainties and behaviour were described. As uncertainties fossil fuel and CO_2 prices, electricity demand, policies, and innovation were explored as these were required for the ABM analysis. Behaviour was explored as this was most relevant in understanding whether an ABM was used. Second, table 4 was filled in based on the findings. Finally, both a predictive scenario and explorative were selected for the ABM analysis.

3.3.2 ABM analysis in EMLab

After the scenarios were dissected, one descriptive and one explorative scenario were analysed. The scenarios that were analysed in detail are the NEV and the OKA. The NEV was analysed because this scenario contains the most technological detail, has the longest history of all scenarios, and is the most prominent. The calculations of the OKA were analysed because recently it has received a lot of media coverage and it is the most recent scenario.

The scenarios were analysed using the Energy Modelling Laboratory (EMLab), which is an open-source Java model (Richstein et al., 2014). EMLab is an agent-based model which aims to analyse the investment decisions of energy producers. These energy producers are the agents in EMLab. They can invest in additional power plants or decommission existing ones. They base their investment decisions on the expected future fossil fuel, CO_2 and electricity prices Additionally, investments by other agents are also considered. Energy companies in EMLab forecast these future prices by using historic data. However, these forecasts are to precisely predict the future. Therefore, decisions made by the energy companies are sub-optimal as they do not possess perfect knowledge of the future.

In order to simulate the intermittency of renewable energy in EMLab, renewable technologies were modelled to produce less electricity during peak hours. Peak hours were defined by splitting the annual load in 20 different time segments which represent the demand fluctuations throughout the year. The reason why EMLab did not contain, for example, the annual availability of wind turbines but instead uses time segments is because this significantly reduces the computing time. Additionally, a version of EMLab was used which did not contain any interconnections with neighbouring countries because some scenarios might not include neighbouring countries.

Power plants have an efficiency, capital, operating and maintenance (O&M) costs, rated capacity, construction time, and fuel efficiency. Furthermore, the change in investment costs and the change in the efficiency of technologies between 2015 and 2030 are based on the WEO 2011 New Policies Scenario. For this research, fossil fuel and CO_2 prices, electricity demand, existing power plants, and capital costs from the scenarios will be used as inputs in EMLab. For some parameters, such as the capital costs of natural gas power plants, numbers are not provided in scenarios. When these numbers were not provided, the values as used in Richstein et al. (2014) were taken.

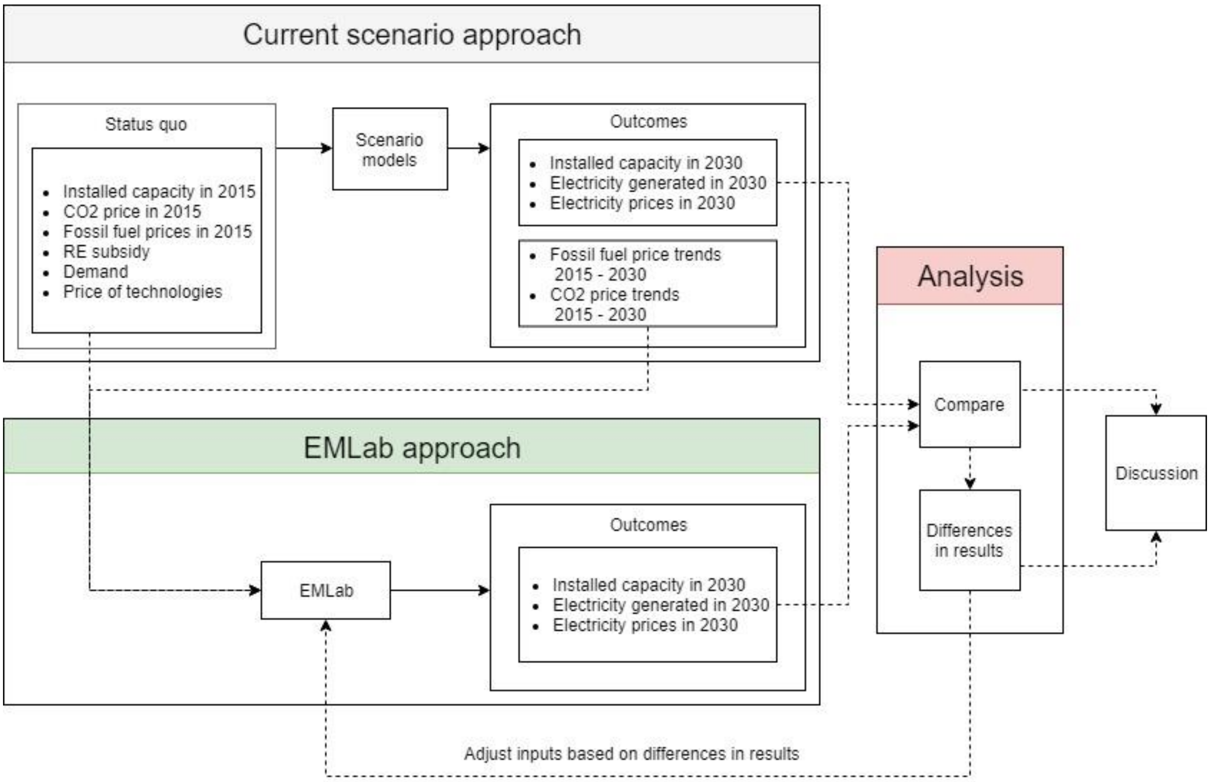

Figure 3. A schematic overview of the methodology.

4 Results

The following sections will present the results of this research. First, the scenarios will be analysed according to the previously presented characteristics in table 1, providing a classification of the scenarios. Second, the results of the EMLab analysis of each scenario will be displayed.

4.1 Scenarios

The next section will classify the previously identified energy scenarios in detail using the characteristics of table 1. To be able to classify the scenarios, the scenarios were decomposed in three steps. Firstly, an introduction for the specific scenarios is provided. Secondly, the uncertainties of each scenario are explored. Finally, the assumptions regarding behaviour that each scenario follows is determined. The classification can be seen in table 4. A complete dissection of the scenarios is provided after the table.

Table 4. Classification of the scenarios.

Characteristic	NEV	SOE	ER	NDE	VE	OKA
General type	Predictive	Explorative	Normative	Normative	Explorative	Predictive
Method	Forecasting	Backcasting	Forecasting	Backcasting	Forecasting	Forecasting
Subject	Area-based	Area-based	Area-based	Area-based	Area-based	Area-based
Timescale	2016-2030	2012-2030	2010-2050	2015-2030	2013-2035	2015-2030
Spatial	Supranational	National	Global	National	Supranational	Supranational
Data	Mostly Quantitative	Mostly Qualitative	Mostly Quantitative &	Quantitative & Qualitative	Quantitative & Qualitative	Quantitative & Qualitative
Level of deviation	BAU	BAU and unconventional disruptions	BAU and unconventional disruptions	BAU and unconventional disruptions	BAU and unconventional disruptions	Unconventional disruptions
Method	Probabilistic approach	Alternative scenario approach	Alternative scenario approach	Alternative scenario approach	Both approaches	Both approaches
Fossil fuel prices	IEA New Policies and Welvaart en Leefomgeving (WLO)	Not defined	IEA Current Policies and own predictions	IEA New Policies	IEA and own predictions	IEA and own predictions
CO2 prices	Taken from WLO	Not defined	Own predictions	Own predictions	Own predictions	Taken from WLO and own predictions
Electricity demand	Constant demand	17.6% increase in demand	Not defined	25% increase in demand	Constant demand and own predictions	5% increase in demand
Innovation	Literature on learning curves for renewables	Expert opinions	Assumptions not clear	Assumes current state-of-the-art technologies	Literature on learning curves for renewables	Literature on learning curves for renewables
Policies	Current policies and planned policies	Current policies	International policies but not specific Dutch policies	Current policies	Different policy pathways	Planned policies
ABM	No	No	No	No	No	No
Models	Optimisation & Simulation	Simulation	Simulation	Simulation	Optimisation	Optimisation

4.1.1 Nationale Energie Verkenning

Introduction

The Nationale Energie Verkenning (NEV) is a scenario for the energy sector in the Netherlands created by various governmental research institutes (Schoots, Hekkenberg & Hammingh, 2017). The Energieonderzoek Centrum Nederland (ECN), PBL, Rijkdienst voor Ondernemend Nederland, and the Centraal Bureau voor Statistiek (CBS) are responsible for the calculations in the NEV. These organizations have been responsible for most Dutch energy scenarios and are therefore rather experienced/ possess a high level of experience. The NEV aims to project the most plausible numbers for the future and has a long history of scenario development. It aims to support decision makers with information regarding the future composition of the energy sector. The NEV is not only focused on the electricity sector but projects for the whole energy sector. It contains two different scenario pathways: one contains the established policies until May 2017, while another also contains intended policies. However, for the electricity production, fossil fuel and CO_2 prices, and installed capacity, both pathways have the same estimates. (Schoots et al., 2017).

Uncertainties

The NEV uses a multitude of models and experts to determine a future which they argue/expect will most likely happen in the future (Van der Welle et al., 2017). Simultaneously, it stresses the fact that models are a simplification of reality and that therefore some nuance might be missing. The NEV tries to determine the impact of such uncertainties by classifying drivers for energy consumption, structural uncertainties, and specific indicators for the electricity sector. Drivers for energy consumption are the population size, the size of the economy, the number of buildings, and car transportation. For the short-term, these drivers are robust, but for medium and long-term uncertainties these drivers can have a large impact on energy demand. More structural uncertainties are energy- and CO_2 prices, innovations, weather conditions, national policy interventions, and external policy interventions. The effect and the size of these uncertainties and their relevance for specific indicators was determined through consulting experts and estimations by various models. The specific indicators are final energy use, final thermal use, energy carrier capacity, renewable capacity, combined heat and power generation, animal populations, and GHG emissions. The uncertainties, the effect they have on these indicators, and what indicators are relevant for different sectors, were used to create upper- and lower bounds for, for example, electricity demand for households. A Monte-Carlo analysis was used on all these different uncertainties to create a specific bandwidth for each value. The

Monte-Carlo analysis was used to create a bandwidth where the 5% and 95% boundary of the Monte Carlo probability-triangle were used to determine the upper and lower boundary of the bandwidth. An import property of the NEV projections is that the actual estimated price is not necessarily the median of the upper and lower boundary of the bandwidth. For example, for the CO_2 price due to the large uncertainties, a bandwidth of 12 to 77 euros per ton CO_2 is used, while the actual predicted price for 2030 is 16 euros per ton CO_2. Additionally, bandwidths for the drivers were also determined by looking at other models and predictions. Especially the Welvaart en Leefomgeving (WLO) and data from CBS is used frequently. One important policy instrument that the NEV analyses is SDE+. The SDE+ is a subsidy instrument that companies or individuals can use to receive a monetary compensation for a multitude of sustainable purposes. According to the NEV, much less wind and solar energy would be installed without this subsidy/ if this subsidy had not existed. Although by then no decision had been made yet to continue the SDE+, the NEV assumed that it will be continued after 2019 (Menkveld et al., 2017).

Fossil fuel prices

To predict/calculate fossil fuel prices, predictions from the World Energy Outlook (WEO) are used in combination with bandwidths from the WLO (Van der Welle et al., 2017). Combining predictions from different outlets can lead to inconsistencies, as noted by the NEV. For example, for the oil prices, the predictions of the actual price are based on the IEA New Policies scenario, while the bandwidth is based on different scenarios from the WLO. For the gas price, the actual price is also based on predictions by the IEA New Policies scenario. However, while the lower boundary of the bandwidth is also taken from the WLO scenario, the upper boundary of the bandwidth is determined from the Current Policies scenario from the IEA. This is because the upper boundary from the WLO scenario would be lower than the predicted actual price in the IEA New Policies scenario. Another interesting observation is the fact that the WLO data predicted prices from 2030 onwards and that these prices are backcasted to 2016 (Van der Welle et al., 2017).

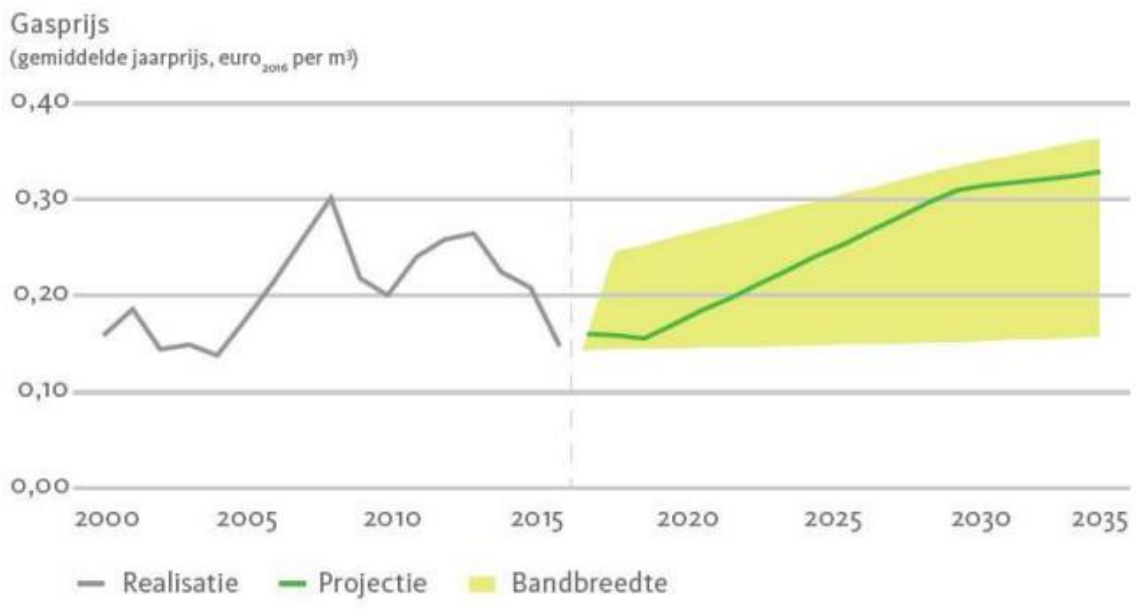

Figure 4. Estimates for gas prices (Schoots et al., 2017, p. 44).

CO_2 price

The CO_2 price in the NEV is determined by a variety of factors. Firstly, the projected price is determined through a least-cost optimisation model for GHG reduction. Secondly, the bandwidth is determined through the combination of expert opinions and other scenarios, most notably the WLO of 2015.

ABM

In principle, ABM is not used for the development of the NEV. However, this does not mean that behaviour itself is absent. Throughout the NEV, the importance of investment behaviour and the role it plays in ensuring renewable targets are highlighted continuously. Furthermore, the role of market behaviour, which is a type of investment behaviour, is argued as very hard to predict. However, for these types of behaviour they are modelled in optimisation models where it is assumed that the system planner has full information and perfect knowledge.

4.1.2 Scenario-ontwikkeling energievoorziening 2030

Introduction

The Scenario-ontwikkeling energievoorziening 2030 (SOE) was developed by CE Delft and DNV GL for the Dutch TSOs in order to facilitate the Dutch Energy Agreement (Rooijers, Schepers, Van Gerwen & Van der Veen, 2014). CE Delft is an independent research institute that is specialized in energy, transport, and natural resources. It aims to facilitate the transition to a sustainable energy sector. DNV GL is a classification society and accredited registrar. It provides expertise on energy and renewables and has been active in the power sector for more than 100 years. The aim of this analysis is to explore five different pathways to a future energy sector composition. These pathways are supposed to support actors in the energy sector with their investment decisions and strategies. Each pathway differs in the number of renewables the future/the energy sector will contain in 2030, the amount of electricity that is generated in a decentralized manner, and the amount of CO_2 reduction each composition will lead to. The different pathways can be seen in table 5 (Rooijers et al., 2014).

Table 5. Components of the different pathways.

Scenario	CO_2 reduction compared to 1990	Renewable electricity	Amount decentralized generation
A	40%	25%	100%
B	40%	25%	<25%
C	55%	25%	100%
D	100%	25%	25%
E	100%	100%	100%
BAU	24%	18%	100%

<u>Uncertainties</u>

In the SOE, the energy sector is analysed from a macro-economic perspective. This analysis is conducted using two different models: the EnergieConversieModel (English: EnergyConversionModel) and the Smart Grid scenario model, also called ‘profielmodel’. No optimisation models are used. Assumptions for uncertainties are made based on expert opinions. For all five pathways, general parameters such as population, GDP, and transport are kept similar. Additionally, the functional electricity demand is similar in each scenario, namely 17.6% higher than the demand in 2012. This is based on predictions by the European Commission’s Energy Roadmap for the whole of Europe for 2050 and the SOE assumes that this will also be the case for the Netherlands. Each scenario has a certain outlook for 2030 and uses backcasting to determine the composition of the energy sector in 2024 and 2018. As data for 2012 is available, data for 2030 is modelled and only two other time occurrences exist in the model, the researchers determined the values for 2018 and 2024 based on the development path of the parameters. See figure 5 for an illustration as provided in the SOE. The legend shows/illustrates the different types of curves that will occur due to these assumptions. A linear path between 2012 and 2018, 2018 and 2024, and 2024 and 2030 can be observed because there are only data points available for these years (Rooijers et al., 2014).

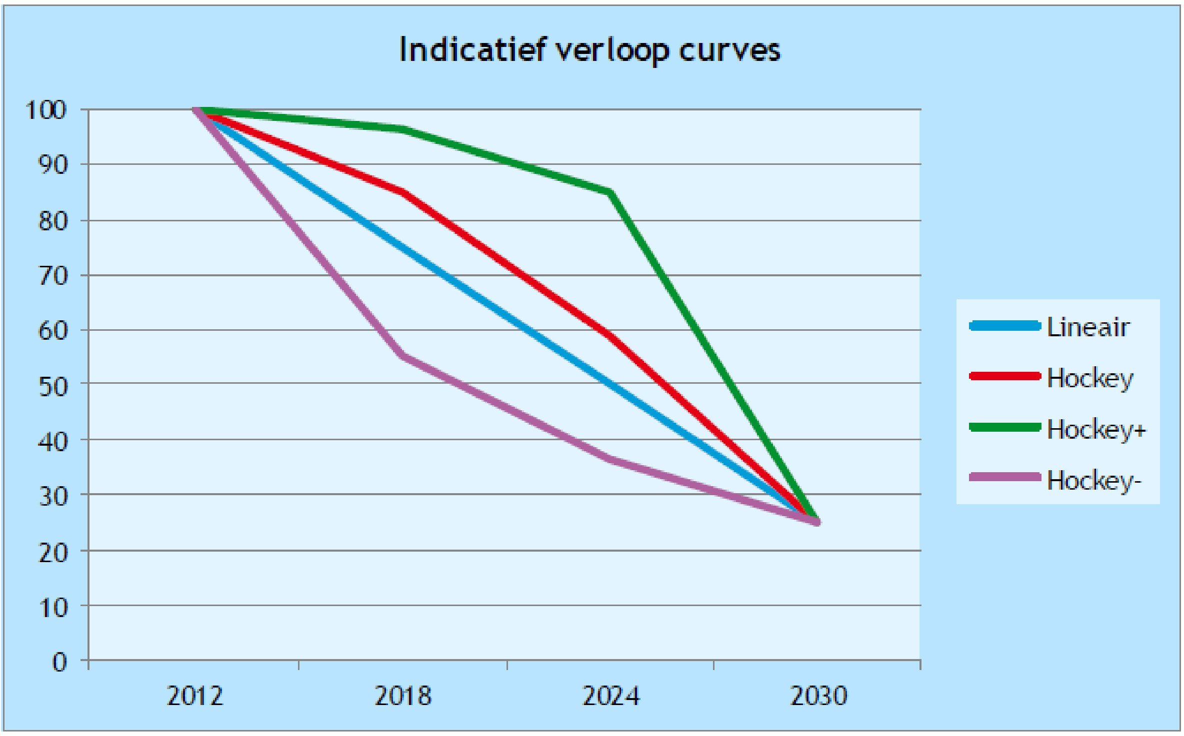

Figure 5. Visualisation of backcasting method (Rooijers et al., 2014, p. 44)

<u>CO_2 and Fossil fuel prices</u>

The backcasting technique that the SOE use in the scenarios in combination with the specific models results in an absence of fossil fuel prices. Since the energy mix in each scenario is based on expert opinions, fossil fuel prices are not required to model or optimize the energy mix in 2030. Additionally, for the same reasons, this also removes the need for CO_2 prices to exist.

<u>ABM</u>

One of the main reasons why the results for the different pathways differ is, according to CE Delft and DNV GL, because more investments occur in some pathways. These investments are made due to the profitability of the energy technology in that specific instance. By combining the Energieconversiemodel and the Profielmodel and based on the specific energy demand for each year, the installed capacity is determined. Unfortunately, no further information was provided regarding these models, but it seems that this is a clear example of optimisation techniques in order to determine the installed capacity. Therefore, we can assume that the models contain one invisible system planner who has perfect information, and who is fully rational.

4.1.3 Energy [R]evolution

Introduction

The Energy [R]evolution (ER) Scenarios from Greenpeace have been published since 2005, and five editions have already been developed (Teske et al., 2013). The 2012 report is the first report specifically for the Netherlands, in which Greenpeace wants to phase out nuclear energy and fossil fuels, as well as reduce CO_2 emissions. Another main goal of Greenpeace is to limit the potential temperature increase to two degrees Celsius compared to pre-industrial levels. The ER is developed in combination with the German Aerospace Agency (DLR). The scenarios run until 2050 but have intervals of 10 years and therefore data for 2030 is also available (Teske et al., 2013).

Uncertainties

The ER contains two pathways: a reference pathway which can be classified as a BAU pathway, and a revolutions pathway. The BAU scenario is based on the Current Policies scenarios from the IEA. It only takes international policies into account and does not incorporate Dutch policies for the future. The revolutions scenario aims to reduce CO_2 emissions to below 4 giga tonnes (Gt) per year by 2050. General parameters such as population and GDP are the same for both scenarios. The revolutions scenario also tries to phase out nuclear energy and limit hydropower and biomass power generation, due to the perceived unsustainability of these resources. Regarding the modelling a distinction must be made between the global report Greenpeace published and the one used for this research which is focussed on the Netherlands. For the global report, Greenpeace used the MESAP model to simulate the supply side, while the PlaNet model was used to determine the energy supply and demand, environmental impacts, and costs (Spataru, 2017). These models contain both top-down and bottom-up aspects (Van Beeck, 1999). For the Netherlands, supply was also modelled using MESAP/PlaNet, but for the demand a study by Graus and Kermeli (n.d.) was used. General parameters such as population, GDP, and GDP growth are kept similar between both the reference pathway and the revolutions pathway (Teske et al., 2013).

CO_2 and fossil fuel prices

The fossil fuel prices estimated by the Current Policies scenario of the WEO 11 were deemed too conservative for the ER. Therefore, they increased these predictions by roughly 5 to 10%. This means that for example the price of oil prices increased to €126 per barrel instead of €112 per barrel. CO_2 prices are estimated based on the ER's own assumptions (Teske et al., 2013).

Behaviour

Behaviour is not extensively covered in Greenpeace's ER scenario. Investments in new technologies are argued to be driven by their long-term financial returns. The MESAP/PlaNet model is not freely accessible but based on a general outline it seems that it does not contain specific actor behaviour for investments (Simon, Naegler, & Gils, 2018; Voß, Schlenzig, & Reuter, 1994). The DLR states that MESAP is not an optimisation model (DLR, 2013). Furthermore, they mention that MESAP depends almost entirely on the settings and input of the modeller. This thus biases the input to the modeller's bounded knowledge.

4.1.4 Nederland 100% Duurzame energie in 2030

Introduction

The goal of Nederland 100% Duurzame energie in 2030 (NDE) scenario is to explore the possibilities for the Netherlands to have a fully renewable energy sector by 2030 (Urgenda, 2017). The scenario was commissioned by Urgenda, which is a Dutch national non-profit organization for sustainability and innovation (Urgenda, 2017). The NDE is constructed through the Energy Transition Model (ETM). The ETM contains two time periods: the present 2015 and an end year 2030 (ETM, 2019).

Uncertainties

The energy mix for the Netherlands is obtained from the IEA, while CBS data is used for generation, demand, and production. Population predictions of the CBS are used, while GDP changes are calculated using projected demand increases. By using two different time periods, the values for the in-between years are interpolated either linearly or exponentially. For some sections of the NDE, there are no values given for the in-between years. This is due to the normative aspects of the NDE where the goal is to reach a specific future. An example of this can be seen in figure 6.

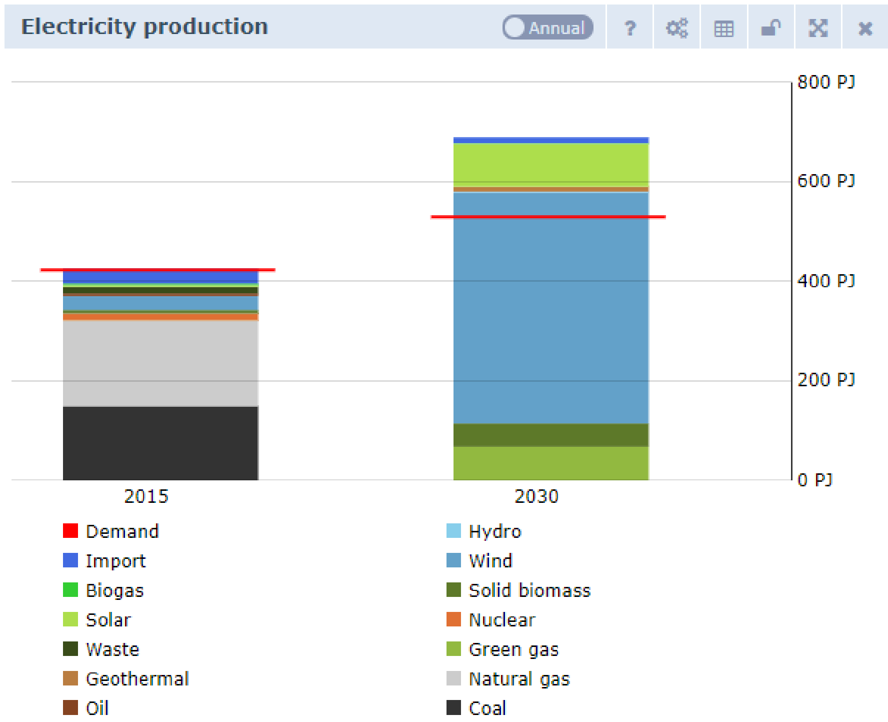

Figure 6. Display of the methodology of the ETM (ETM, 2019).

Fossil fuel and CO_2 prices

Coal, natural gas, and oil prices are determined using the IEA WEO 2013 New Policy scenario. Biomass and CO_2 prices were determined by consulting various experts from the electricity sector (Urgenda, 2017).

Behaviour

In order to reach the targets of the NDE, the NDE assumes consumer behavioural changes in their transportation needs, consumption habits, and many other factors. Many of these behavioural changes relate to energy demand or sustainable lifestyles for consumers. However, investment behaviour is not modelled. This can be seen in the fact that the ETM allows the operator to set the number of wind turbines for 2030, instead of being able to determine behaviour and thereby calculating the number of possible wind turbines in 2030. The NDE does mention that the greatest challenges surround the industry but does not explore the behaviour of industry in detail. The ETM does have options for adjusting consumer behaviour. These are turning off applications, lights, heating, and washing at low temperatures. However, this behaviour only influences demand and these values are set by the modeller and depend on the modeller's own interpretation (Urgenda, 2017).

4.1.5 Verkenning energievoorziening 2035

Introduction

Next to being part of developing the NEV, the ECN is also the owner of the Verkenning energievoorziening (VE). The VE aims to go beyond the business as usual approach of the NEV by incorporating new progressive climate policies. Four different pathways are analysed, with different degrees of renewability. The contents of these pathways are based on story lines that were determined by the European Network of Transmission System Operators (ENTSO). For the first pathway the NEV of 2016 is used. The second pathway is a combination of the NEV 2015 with more policy interventions. The third pathway is focused on central renewable energy production, while the fourth pathway is focused on decentralized renewable energy production.

Uncertainties

General parameters such as GDP and population are kept similar for all pathways. However, energy demand is not similar in the different pathways because each pathway has/uses/contains different energy saving mechanisms. Different policy uncertainties are incorporated in the different pathways; for example, some pathways phase out coal after some time. Similar methods as for the NEV are used to determine demand and production, which is most likely caused by the fact that both reports use the COMPETES model. In general, this scenario is fairly similar to the NEV 2017, although less detailed. This is because they were constructed for different purposes. The VE aim is mostly to explore possible pathways for the future, while the NEV 2017 explores the most likely composition of the future.

Fossil fuel and CO_2 prices

Many of the uncertainties are dealt with by the existence of the different pathways. For example, for the CO_2 price, scenario 2 has a price of €20/tonne of CO_2, while scenario 3 and 4 have a price of €82/tonne of CO_2. No explanation is provided for how these values are determined. These values are most likely determined by own predictions, as both the NEV 2015 and the NEV 2016 do not foresee a price of €82/tonne CO_2. For fossil fuel prices the same situation is present, with coal prices ranging from 2,4 €/GJ to 3,5 €/GJ in 2030 and 7,8 €/GJ to 10,5 €/GJ in 2030 for natural gas.

Behaviour

ECN does not mention behaviour in the VE scenario. The COMPETES model that they use has an investment component that optimizes investments. In the next scenario, the workings of COMPETES are explained.

4.1.6 Calculations of the Klimaatakkoord

Het Klimaatakkoord (OKA, English: Climate agreement) is an agreement which aims to reduce CO_2 emission by 49% in 2030 compared to pre-industrial levels. The agreement itself encompasses much more than the electricity sector and was developed by splitting the process of reaching the target into several sector tables. The relevant table for this study is the electricity table, which was created by members from industry, non-governmental organisations, governmental bodies, and unions. The OKA itself is not classified as a scenario because it mostly contains goals and targets for the members who signed the agreement. However, the OKA has been analysed by PBL and CPB in 2019 as requested by the Minister of Economic Affairs and Climate Policy in order to determine what impact the measures in the OKA will have (Van Hout et al., 2019). This analysis therefore represents an important energy scenario for the Netherlands.

Uncertainties

The OKA contains two different scenario pathways: a basic pathway (KA-basis) and an actual prices (KA-act) pathway. For the basic pathway the fossil fuel and CO_2 prices of the NEV were used. The actual prices contain new insights for the development of fossil fuel and CO_2 prices. In order to determine the costs of wind and solar energy in the future, a literature review was conducted for the OKA. The effect of subsidies on renewable investments was also determined. The OKA also uses the COMPETES model similarly to the NEV and the ECN.

Fossil fuel and CO_2 prices

For the OKA itself, the fossil fuel and the CO_2 prices were taken from the New Policies scenario from the WEO. For the analysis of the OKA it is unclear whether these prices were also taken from the New Policies scenario. Especially the prices for CO_2 emissions are higher in the OKA analysis compared to the OKA itself

Behaviour

The OKA explains in detail how the investment module of COMPETES works. It explains that it is an optimisation method, where the installed capacity is determined based on the demand for electricity. COMPETES looks at the years 2020, 2025, and 2030. If a power plant is unable to be profitable in at least two of these time periods, it is decommissioned. If more capacity is needed, investments are made based on the assumption that perfect information is available and that all actors are fully rational. The OKA explicitly states that this assumption leads to inaccuracies, as actors will not operate rationally in reality. Important to note is that the renewable installed capacity is an assumption. Additional investments into renewables are not taken into consideration.

4.1.7 Synthesis of scenarios

Method

The scenarios have various similarities. Many of the models have a long history such as the MESAP/PlaNet model and the models used for the NEV, VE, and OKA. An overview of all used models can be found in figure 7.

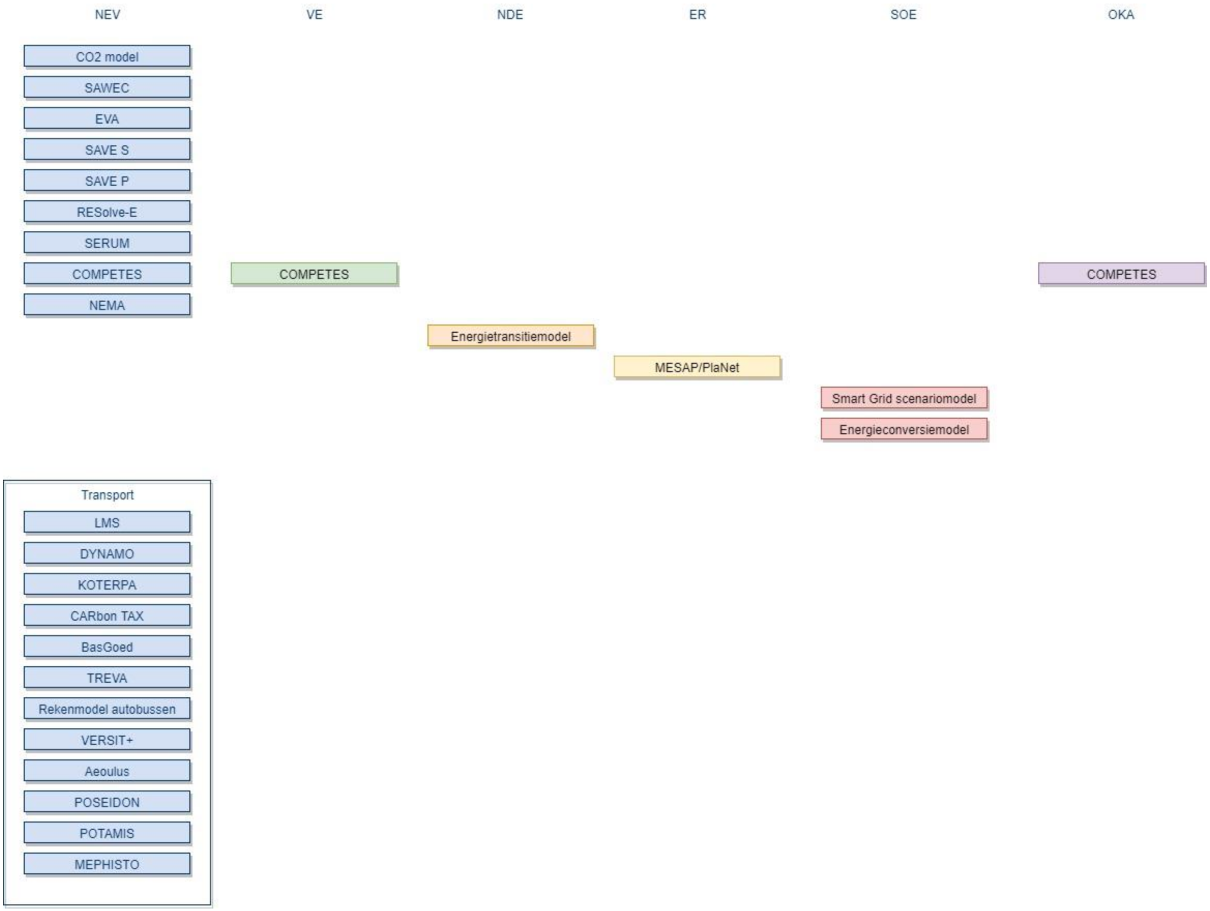

Figure 7. Visualisation of the different energy models used by the scenarios.

Agent-based models are not used for the development of any of the scenarios. The scenarios either use optimisation models to optimise the energy fix for 2030, or simulation models which simulate a possible energy mix based on the modeller's own assumptions. Finally, the effects of uncertain behaviour are not modelled for the scenarios and none of the scenarios contain multiple actors who can invest.

Distinctions can be found in the methodologies that are used in the models to construct the scenarios. The NDE and the ER are both normative scenarios as they have a target for 2030 that is determined by the scenario developers. The SOE, VE, and KA are all explorative scenarios as they explore how the future would develop if certain measures are taken. The NEV is a predictive scenario as it looks at the current situation and explores how this would develop in the future. All scenarios make assumptions for interconnectivity, where the neighbouring countries serve as a buffer. During shortages, these countries will deliver electricity and during hours where excess electricity is generated in the Netherlands, these countries will import this electricity. Interconnectivity seems to be difficult to incorporate for the various scenarios. The SOE assumes that other countries have similar climate policies as the Netherlands. The NDE does not incorporate interconnected countries in the Dutch merit order. The ER does not elaborate on how they include interconnectivity and it seems that their focus is primarily on the import and export of fuels required for electricity. The NEV takes a close look at the political climate in the neighbouring countries and uses the ENTSO-E predictions to determine the future interconnected capacity. It constructed two small-scale scenario pathways specifically for how import and export of electricity would change depending on changes in neighbouring countries. Even though the NEV explores the effects of interconnectivity the closest of all scenarios, it does stress that neighbouring countries cause a great deal of uncertainty for the Dutch electricity balance.

Uncertainties

In general, uncertainties are treated differently in the different scenarios. The NEV contains the most detailed method to account for uncertainties, as a Monte-Carlo analysis is used to determine the bandwidth of possible values for a specific prediction. The OKA and the VE use the NEV as a foundation for their analysis and therefore most likely also use some of the uncertainty mitigation tools of the NEV. For the other scenarios, uncertainties are mitigated by own assumptions, academic research, or other scenarios. For future fossil fuel and CO_2 prices, the WEO is used in almost all scenarios. However, a difference exists in which pathways of the WEO are used. The NEV, NDE, SOE, and OKA use the New Policies scenario by the WEO, while the ER uses the Current Policies scenario as a benchmark. Although the approach of the VE is very similar to the NEV, the VE uses own predictions for fossil fuel and CO_2 prices.

Policies

Policies are also treated differently in the various scenarios. The scenarios originating from governmental sources, NEV, ECN, and OKA, have a strong focus on policies and in what way they can influence the future. The other scenarios have a smaller focus on policies, and for example the ER only looks at international policies.

Demand

Electricity demand projections are different for the scenarios. All scenarios argue that the demand is caused by changes in GDP, population, and innovation. While the NDE, SOE, ER, and OKA foresee a slight increase in electricity demand ranging from 5% to 25% compared to their reference year, the NEV does not foresee significant change in electricity demand. The NEV, SOE, and ER use a constant electricity demand for all their pathways. The VE and NDE use different electricity demands to explore how these influence the outcomes.

Innovation

Innovation is also treated differently for all scenarios. The NEV and the VE use a detailed analysis on the learning curves of certain technologies such as solar power and incorporate these in their predictions. SOE uses expert opinions to determine the innovations in the electricity sector. For the ER the innovative assumptions are unclear, which most likely indicates that it uses present technologies. NDE uses a conservative approach to innovation and assumes that current state-of-the-art technologies will not be improved for the future.

Status quo

The installed capacity at the reference year that all scenarios use is based on CBS data for that particular year. For the SOE 2012, for the ER 2010, for the NEV, VE, and OKA, 2015 is used. The NDE used 2013, but since the ETM is updated regularly, the current model has been updated to 2015. For current fossil fuel prices, the NEV, VE, NDE, OKA, and ER use the WEO. The reference for current CO_2 prices is often not clear. The NEV and ECN do specify that the CO_2 prices originate from Point Carbon. It seems that all scenarios use detailed sources for the present situation and that no issues are present here.

ABM

Agent-based models are not used for the development of any of the scenarios. The scenarios either use optimisation models to optimise the energy fix for 2030, or simulation models which simulate a possible energy mix based on the modeller's own assumptions. Finally, the effects of uncertain behaviour are not modelled for the scenarios and none of the scenarios contain multiple actors who can invest.

4.1.7.1 Summary scenario estimates

Even though it was not the aim of this research to provide an overview of the scenario estimates, it is still relevant information. Therefore, an overview of the different pathways, the different capacity estimates, and the different fossil fuel and CO2 price estimates are displayed.

In figure 8, the different aims of the pathways are displayed. In order to provide an overview of the scenario estimates for the BAU and the 100% renewable pathways, the scenario estimates are presented together in the following paragraphs.

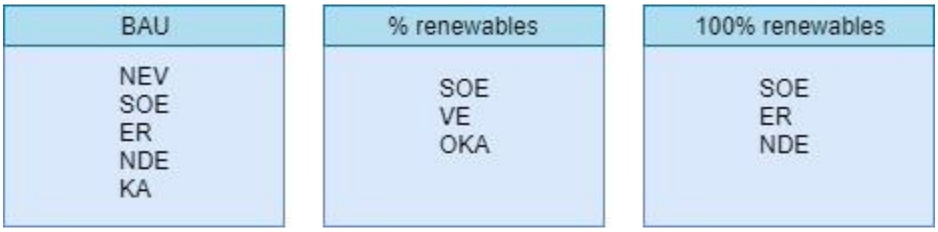

Figure 8. Different aims of the scenario pathways.

Figure 9 displays the electricity generated in peta joule (PJ) for the BAU pathways of the NDE, RE, NEV, SOE, and KA in 2030. The RE, NEV, SOE, and KA-act all predict similar amounts of electricity generation in the Netherlands. For this figure import and export were not incorporated so therefore the NDE could also have a similar demand for the Netherlands if their estimated imports cover the differences with the other scenarios. The NDE, RE, and SOE all foresee a large role for natural gas in the future if the BAU situation is continued. Compared to 2015, the KA-act and the NEV foresee a sharp increase in electricity generation by renewable sources. Especially wind power will be responsible for more than 50% of all electricity generated in the Netherlands.

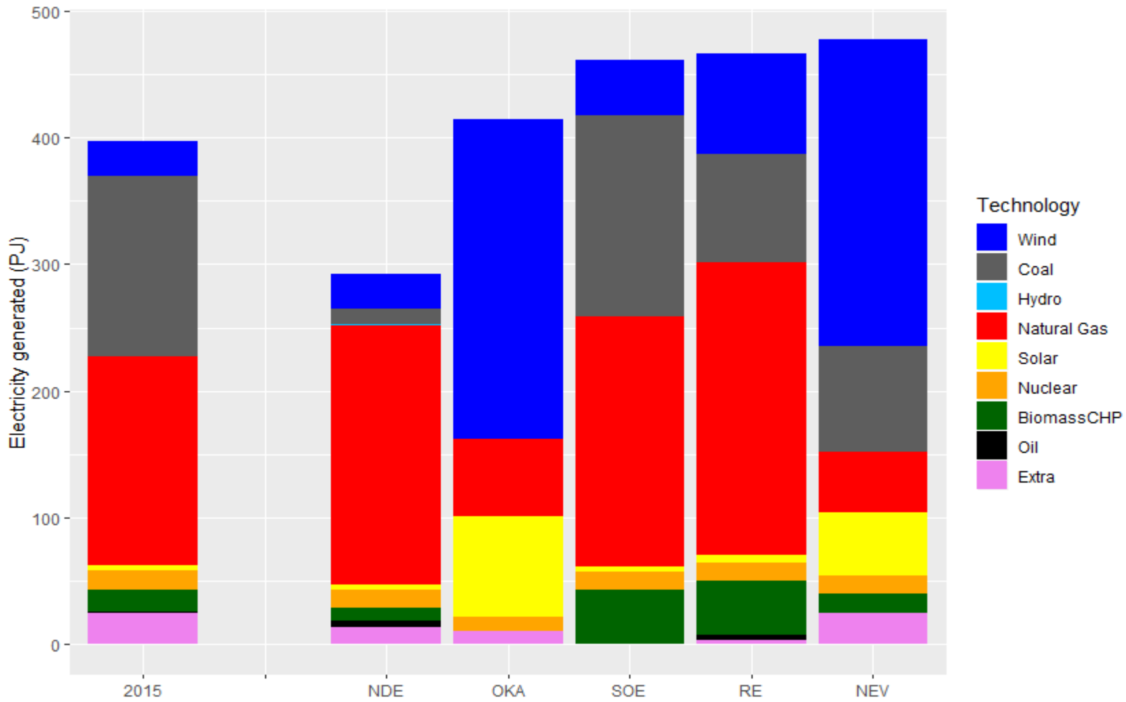

Figure 9. Different types of electricity generated for the BAU pathways in 2030 compared to the 2015 baseline.

When looking at figure 10, the electricity generated in the various 100% renewable pathways of the different scenarios is displayed. The largest difference between these pathways and the BAU pathways is that all the 100% RE pathways estimate the Netherlands to generate more a lot more electricity 2030 than the BAU pathways do. The reason why the ER still contains fossil fuels, while the other scenarios do not, is because the goal of the ER was to have a fully carbon neutral society in 2050, while the other scenarios aimed to achieve this target in 2030.

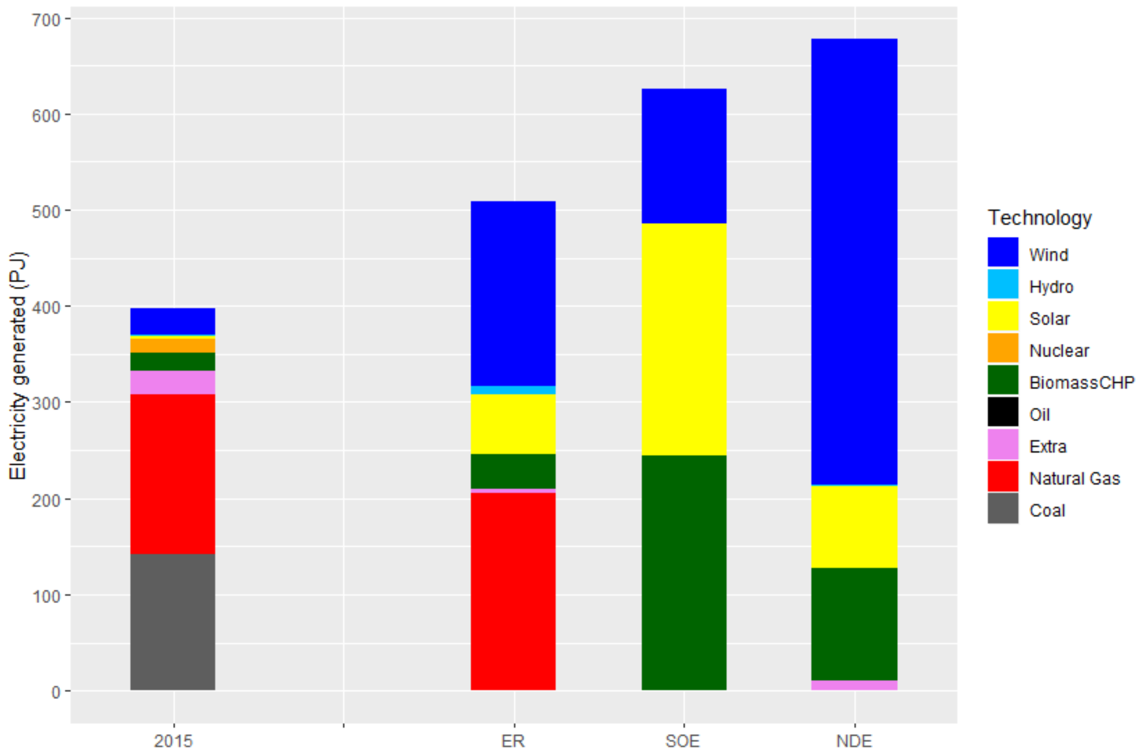

Figure 10. Different types of electricity generated for the 100%RE scenarios in 2030 compared to the 2015 baseline.

In figure 11 the installed capacity can be seen for the BAU scenarios and the installed capacity in 2015. The scenarios have different generation portfolios. The NDE and the SOE see a slight increase in installed fossil fuel capacity, while the NEV, the KA-act, and the ER estimate a decrease in installed fossil fuel capacity. The scenarios that have a greater installed capacity for renewables also have more total installed capacity than the scenarios who do not. Another noticeable trend in the figure can be seen in the estimate for the NEV and the KA-act, namely that a large portion of the generation portfolio is covered by solar power, something which was not present in 2015.

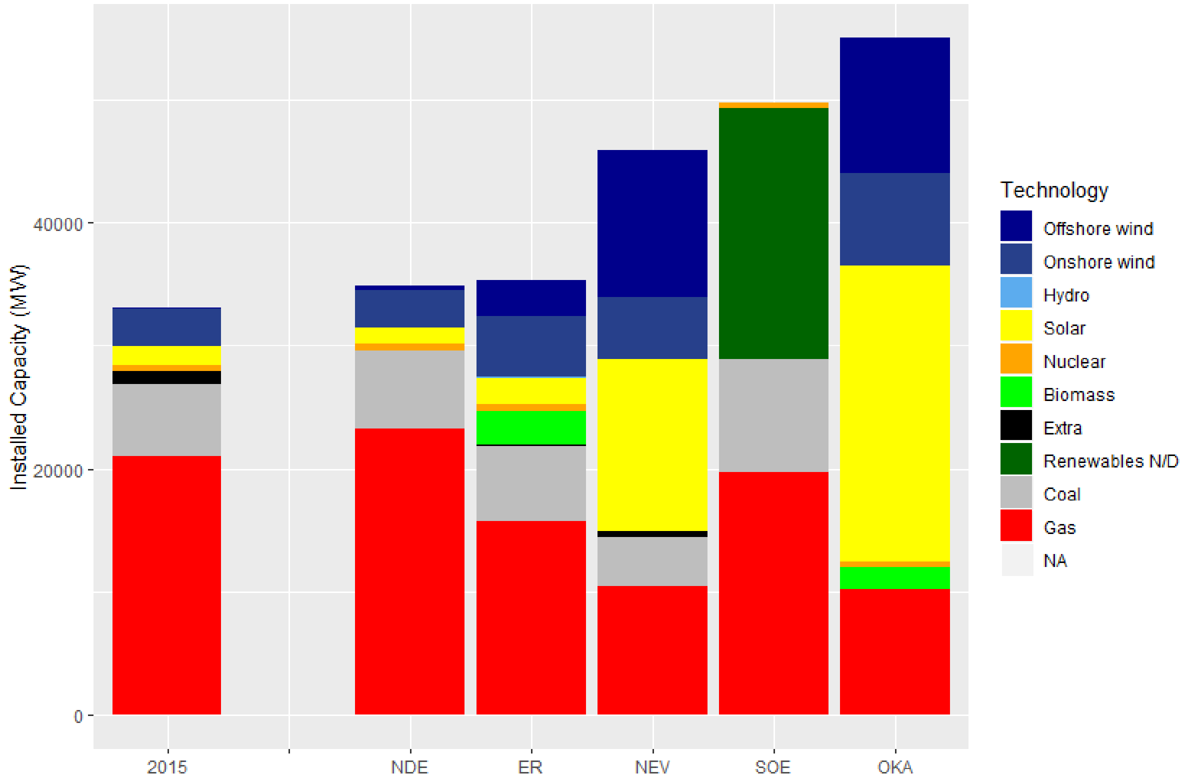

Figure 11. Different types of installed capacity for the BAU pathways in 2030 compared to the 2015 baseline.

In figure 12 the installed capacity for the 100% renewable scenarios can be seen compared to the 2015 situation. What becomes apparent is that the scenarios estimate a much greater installed capacity in 2030 compared to 2015. Except for the ER scenario, the other scenarios contain barely any fossil fuel technologies. For the ER there is a noticeable amount of natural gas installed capacity. Although this is mentioned to be CHP generated, it is classified as a fossil fuel technology in the ER itself and deliberately not associated with biomass CHP.

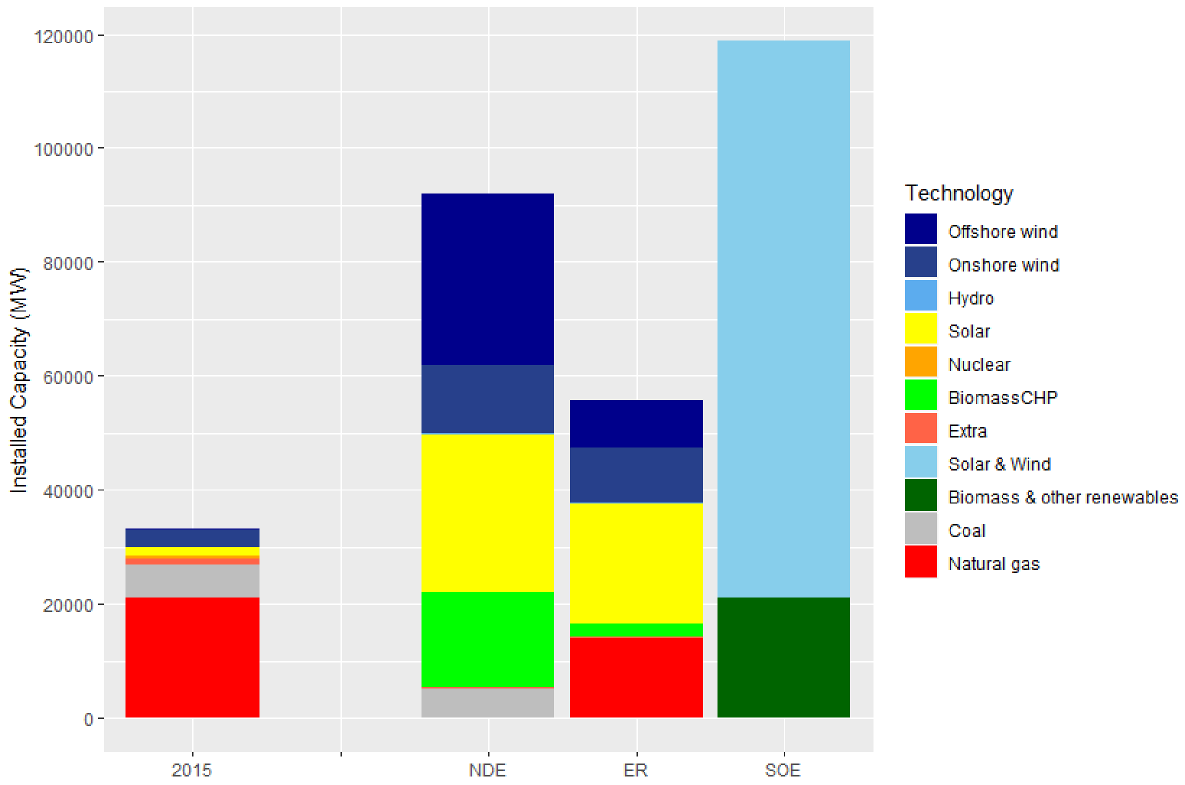

Figure 12. Different types of installed capacity for the 100RE pathways in 2030 compared to the 2015 baseline.

In figure 13 the price of a tonne of coal is plotted. The prices differ greatly between the scenarios. All scenarios estimate the price of coal to increase in the future except for the NDE, which assumes a sharp decrease. The linearity of the prices is explainable by the fact that many scenarios did not provide data for each individual year. Therefore, the values between these years were interpolated.

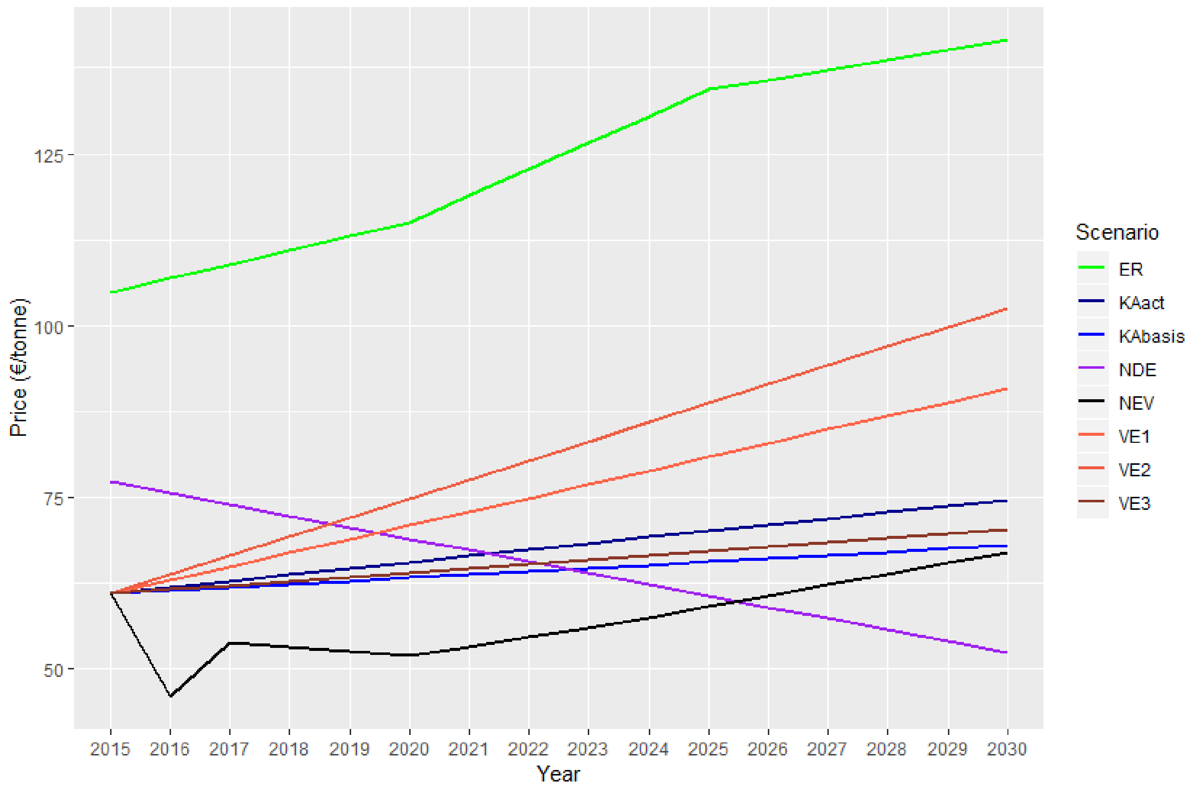

Figure 13. Estimates for coal prices

In figure 14 the price per m^3 of gas is displayed. Almost all scenarios have similar estimates for the price of natural gas between now and 2030. A reason why the ER values could be much higher compared to the others could be because the ER estimated the price in 2010, when natural gas had had a much higher price in 2015 compared to the actual price, and thereby leading to higher estimates for 2030.

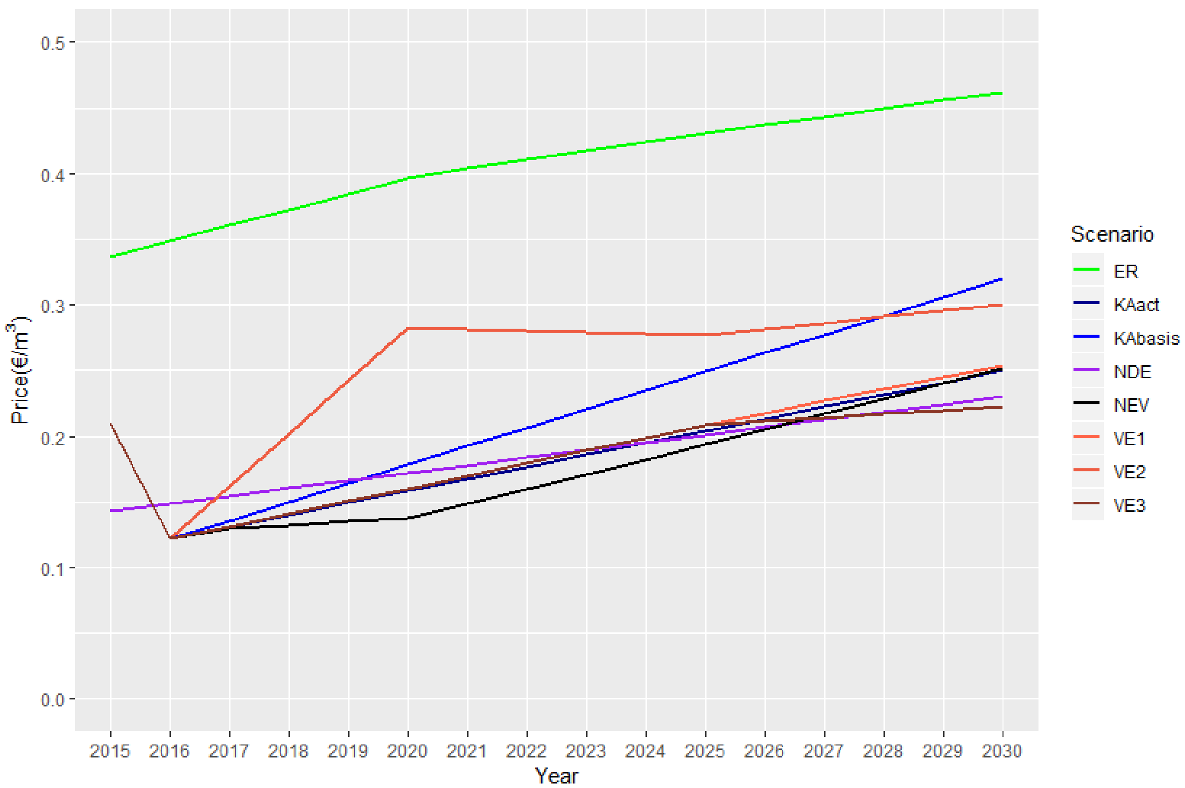

Figure 14. Estimated for gas prices

In figure 15 the estimates for CO_2 prices are displayed. Great differences in the estimates exist, with prices ranging from 16 euros per ton to 90 in 2030.

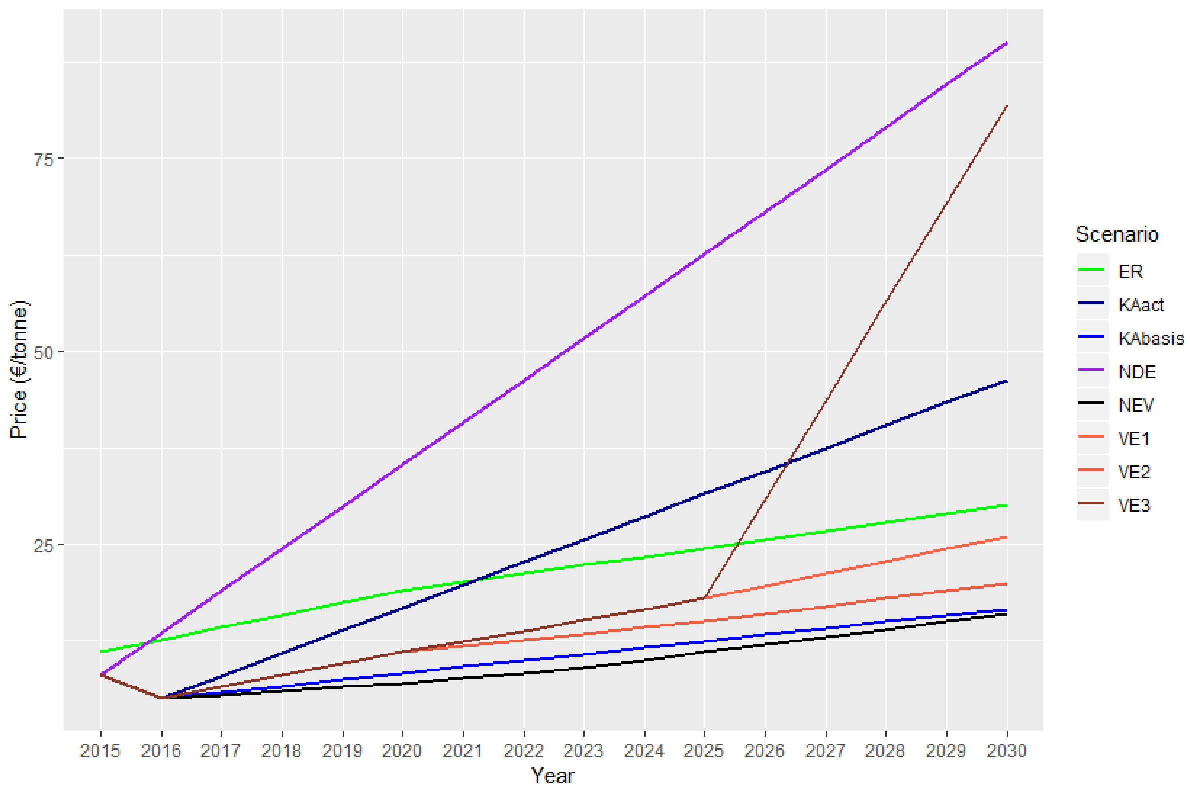

Figure 15. Estimated CO_2 prices.

5 Agent-based modelling results

Before conducting the analysis of these scenarios, it was ensured that the input parameters for the scenarios were similar to the input parameters for EMLab. Firstly, for the fossil fuel and CO_2 prices in EMLab, random trends are used in order to simulate uncertainties. However, scenarios clearly define what fossil fuel and CO_2 prices they expect to see for the future. Therefore, these trends were adjusted in order to imitate linear or exponential trends which are used in the scenarios. The starting value of this linear trend was the same as the value the scenarios used for 2015. Next, the steps in the linear trend were changed such that in 15 years (i.e. ‘ticks’ in EMLab) the value in 2030 that the scenarios assume, should be reached. This created a linear price development that has the same starting and ending value in EMLab as the scenarios.

Secondly, the installed capacity in EMLab was set equal to the installed capacity used for the scenarios. As this analysis used 2015 as the starting date, the capacity in EMLab was harmonized to the capacity in 2015. Thirdly, the capital and O&M costs as defined in the scenarios were used in EMLab for 2015. Fourthly, scenarios contain a variety of policy instruments, of which the most important for this research are renewable subsidies. In order to incorporate these subsidies in EMLab, a specific agent was used. This agent is called a ‘target investor’. This target investor sets the specific renewable target for a year and invests into these technologies in case the companies do not meet this target. If the companies already construct enough capacity of this technology, the target investor does not invest. This agent was used when either additional renewable capacity between 2015 and 2030 was already planned, such as for wind power, or when the EMLab results were not the same as the scenarios and additional investments had to be made.

Once the initial conditions for EMLab were calibrated to the starting conditions used by the scenarios, the outcomes were compared in R studio. This comparison was made on the installed capacity, electricity produced, and electricity prices in 2030 between EMLab and the scenario in question. As this study aims to show the benefits of ABM in addition to current scenarios, parameters were changed when EMLab did not reach similar values as the scenario. The reason for this is that, when the outcomes are not the same, this might be caused by the inclusion of uncertain behaviour in EMLab. In order to determine the exact role of this behaviour, while also finding options how this behaviour can be influenced so that the estimates of the scenarios are reached in EMLab, the results of both models must be the same. Parameters that could be changed were the price of constructing new power plants (capital costs), fossil fuel prices, and other policy options such as a ban on constructing additional fossil fuel technology.

The NEV and the OKA were selected for the EMLab analysis. The NEV was selected because the scenario contains the most detail, is the most prominent scenario, and is the foundation for much research and other scenarios for the Netherlands. The OKA was selected because it is the most recent scenario and because it has gained a lot of attention in the media. As mentioned before, the OKA contains two pathways. For the analysis, the KA-actual prices (KA-act) was used.

Both scenarios use CBS data for their installed capacity in 2015. They also use planned wind power projects to estimate the installed wind capacity in 2030. The costs of investing in renewable technologies are not clearly defined in the NEV. Therefore, recently published literature on these costs for the Netherlands was for the initial costs. The KA-act does clearly define the investment costs and these values were used initially to try to reach the KA-act estimates.

In the KA-act, coal power plants must be decommissioned in 2020, 2024, and 2030. In order to simulate this in EMLab, while also providing the agents with this knowledge in advance, the lifetime of these coal power plants was changed so that they would be decommissioned in these years. This made also sure the agents knew when a specific power plant would be removed from the market.

For the analysis, firstly the installed capacity was analysed by using the investment values as defined above. For the fossil fuel investment costs, the values by Richstein et al. (2014) were used. When these values were unable to mirror the installed capacity of the scenarios in 2030 in EMLab, parameters were changed. Firstly, the price of solar was adjusted so that the installed solar capacity in 2030 in the EMLab approach was conform the scenario estimates. Then, fossil fuel prices were adjusted in order to try to reach the estimates for installed capacity of natural gas in EMLab. If these adjustments did not work, other measures such as a ban on natural gas investments or further price adjustments of natural gas investments were used.

As explained in the methodology, the hours of a year are split into time segments in EMLab. This was done in order to reduce computing time and to mimic the intermittent nature of renewables. The size of all segments is not the same in order to have enough accuracy to identify peak hours. In table 6 the percentage of the whole year each segment represents can be seen. Segment 1 contains the highest loads, while segment 20 contains the lowest loads.

Table 6. Information regarding the usage of segments.

Segment	Percentage of the year (%)
1	0.01
2	0.11
3	0.58
4	6.57
5-17	6.57
18	6.57
19	0.58
20	0.12

For each scenario in order to try to amplify the effect of uncertain behaviour, two types of analysis were conducted. First, one analysis was conducted where the electricity demand was according to the estimates of the scenario. For the NEV this is a constant demand between 2015 and 2030, while for the KA-act there is a 5% increase in 2030 compared to 2015. Second, an analysis was conducted where the electricity demand was increased by 15%. When two graphs are presented side-by-side, the graph on the left corresponds to the demand as estimated by the scenario, while the graph on the right corresponds to the increased demand. The analysis for the constant demand will be called constant demand. The 15% increase in 2030 compared to 2015 will be called the increased demand.

Each analysis was conducted ten times in EMLab in order to mitigate the effect of outliers. From these ten runs the average was used for all the visualisations.

5.1 NEV

The next section shows the EMLab analysis of the NEV estimates. The input parameters from the NEV were used as inputs for EMLab. This means that the installed capacity in 2015, the fossil fuel and CO_2 prices, capital costs, and O&M costs from the NEV were used. Then, if the final installed capacity in 2030 in the EMLab results was not similar to the NEV estimate for 2030, these inputs were changed. In order to improve visibility a summary of the values in the figures can be seen in table 7 and for the production in table 8 at the end of the chapter.

5.1.1 Installed capacity

In figure 16 the installed capacity in the NEV business as usual situation is displayed. This figure was constructed by using the values in the NEV itself for 2015, 2020, 2023, and 2030. The values for the years between these years were determined by interpolating between the data. Almost 50 GW installed capacity is present. Natural gas declines greatly, from roughly 21 GW installed capacity in 2015 to 10.5 GW in 2030. Coal decreases slightly, solar and wind power both increase greatly compared to 2015. The growth in installed wind capacity is caused by the increase in offshore and onshore wind.

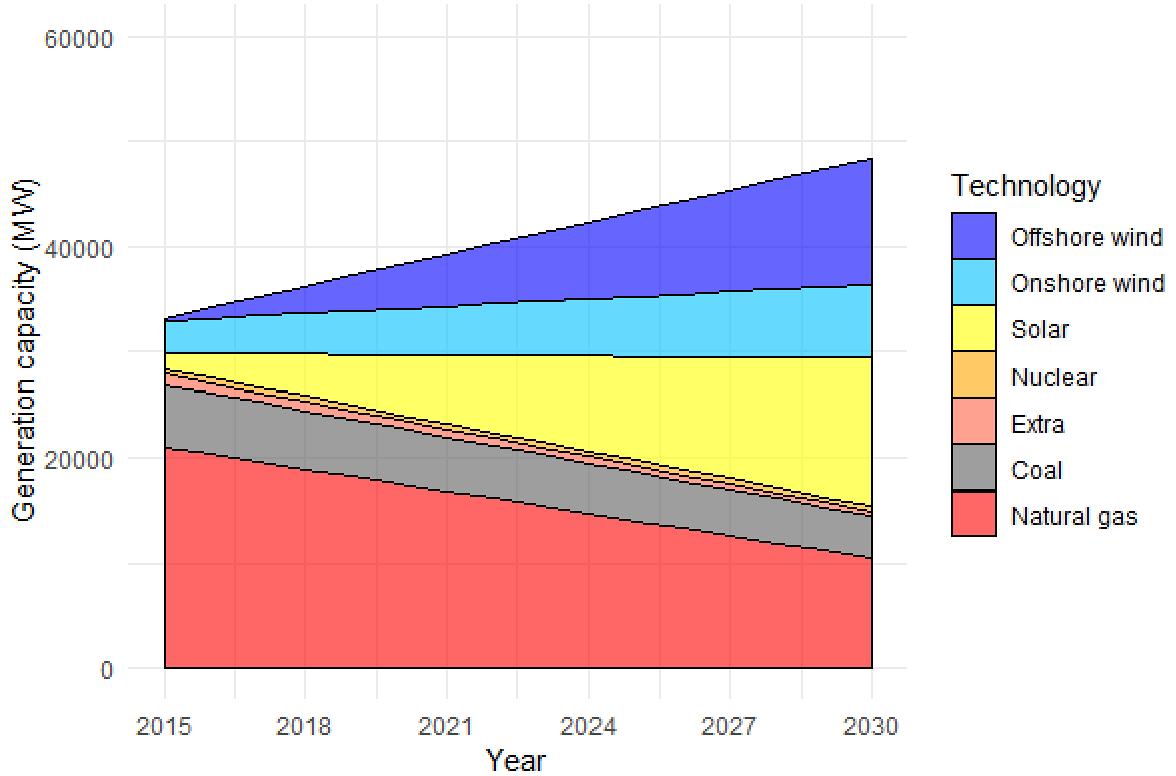

Figure 16. NEV estimates for the installed capacity.

The production for the NEV can be seen in figure 17. It shows that the NEV estimates that the electricity generated by wind power will increase rapidly between 2015 and 2030. Similarly, solar sees an even greater percentage increase between 2015 and 2030. Biomass is fairly constant, with some peaks occurring in the mid 2020's. Coal gradually decreases, from 142.3 PJ in 2015 to 83 PJ in 2030. Natural gas decreases from 165.2 PJ in 2015 to 47.7 PJ in 2030. The total renewable production in 2030 is 307 PJ, while the fossil production is 171.4 PJ. The NEV assumes that electricity demand will be constant from 2015 until 2030. On the other hand, figure 17 displays the production, which is not constant. This is because the NEV estimates that the Netherlands will be an electricity exporting country in 2030. In order to accurately portray the EMLab results of the NEV, both the estimate that demand is constant, while also that production increases are displayed. This production was used as an indicator for demand growth, where the change in total produced electricity was used as demand change. For the next section, both these demands were used where the constant demand was used for the figures a, while the changing demand was used for figures b.

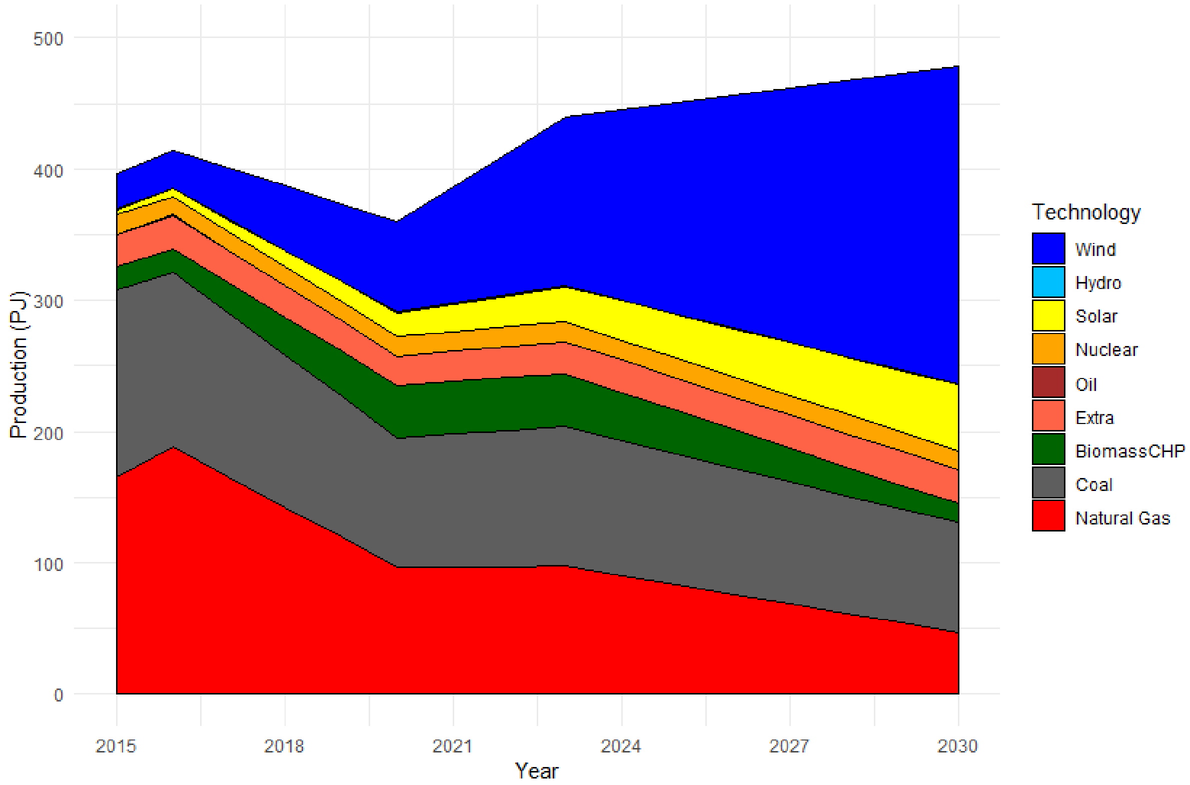

Figure 17. NEV estimates for electricity production.

In figure 18 the installed capacity in the EMLab analysis is displayed. The CO_2 and fossil fuel prices, and installed capacity in 2015 from the NEV were used as inputs for EMLab. Additionally, for capital and O&M costs, figures from literature were used (Richstein et al., 2014; Spruijt, 2015). In order to mimic the subsidies for wind energy used in the NEV, the target investor in EMLab was made to invest so that the wind capacity estimate in 2030 from the NEV would be reached by EMLab as well. No renewable subsidies for solar were used and the price for investing in solar energy was €1/W (Spruijt, 2015). The price for investing in offshore and onshore wind was taken from the NEV and literature (Van Hout et al., 2019).

Except for the investments into wind energy by the target investor, no additional renewable capacity is commissioned. Furthermore, additional natural gas capacity is constructed while this is not the case for the estimates by the NEV itself. Additionally, the total installed capacity in figure 18 is almost 10GW lower than the NEV estimates.

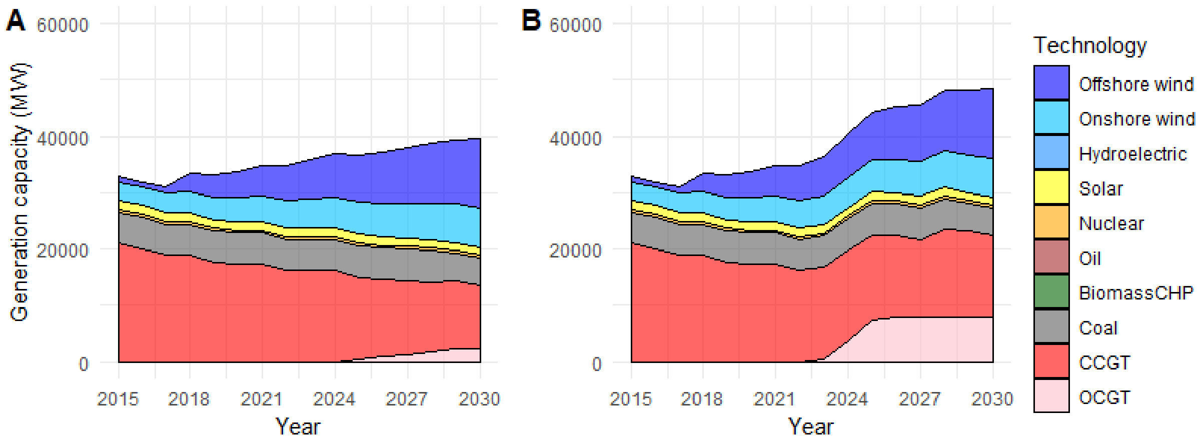

Figure 18. Initial EMLab analysis of the NEV for the installed capacity.

In figure 19a the price for constructing additional solar capacity was reduced to 0.35 €/W, as for this price the EMLab results were similar to the NEV estimate for installed solar power. The growth in installed solar PV capacity is not linear and it takes several years before large investments are made. In figure 19b. the price for constructing additional solar capacity had to be reduced to 0.325 €/W in order to reach the NEV estimates in 2030.

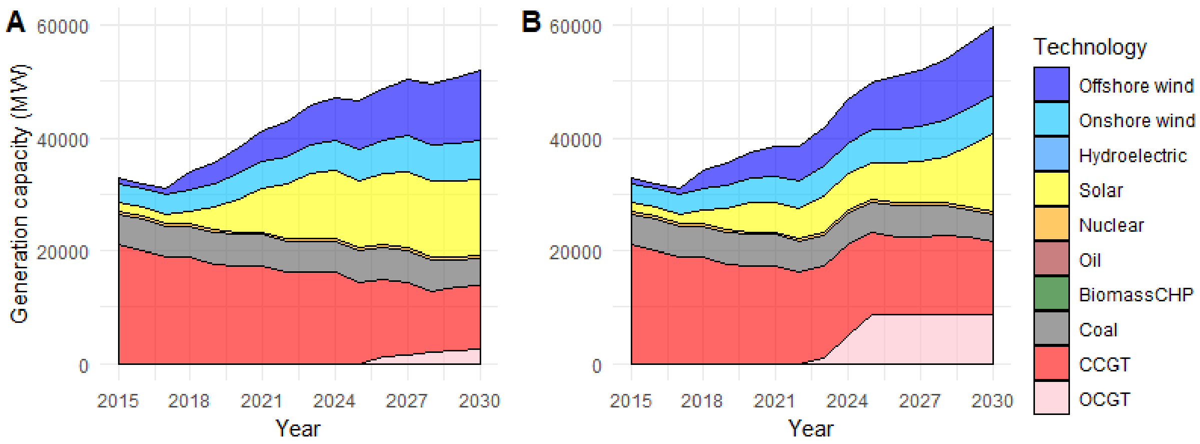

Figure 19. EMLab analysis of the NEV for similar solar capacity in 2030.

Figure 19 does not display the same values for OCGT and CCGT as the NEV estimates. In order to try to reach the NEV estimates for natural gas prices in EMLab, the gas prices were doubled compared to the estimates by the NEV. This means that instead of a linear increase from 0.15 €/m^3 in 2015 to 0.31 €/m^3 in 2030, the price was linearly increased to 0.62 €/m^3 in 2030. As can be seen in figure 20, these prices were unable to limit investments in natural gas.

Therefore, in order to reach the NEV estimates for installed natural gas capacity in 2030, for figure 21 no investments in gas technologies were enabled in EMLab. Figure 21 shows that without gas investments more solar power is installed compared to NEV estimates. Therefore, for figure 22 the capital costs of solar power were increased to respectively 0.395 €/W and 0.36 €/W. For these prices, the NEV estimates were almost reached in EMLab. The difference in the results for 2030 is that the NEV estimates do contain 800 MW less coal installed capacity in 2030 than the EMLab results. However, the NEV estimates contain 800 MW more natural gas installed capacity in 2030 than the EMLab results and therefore it is assumed that this difference is irrelevant as these differences cancel each other out.

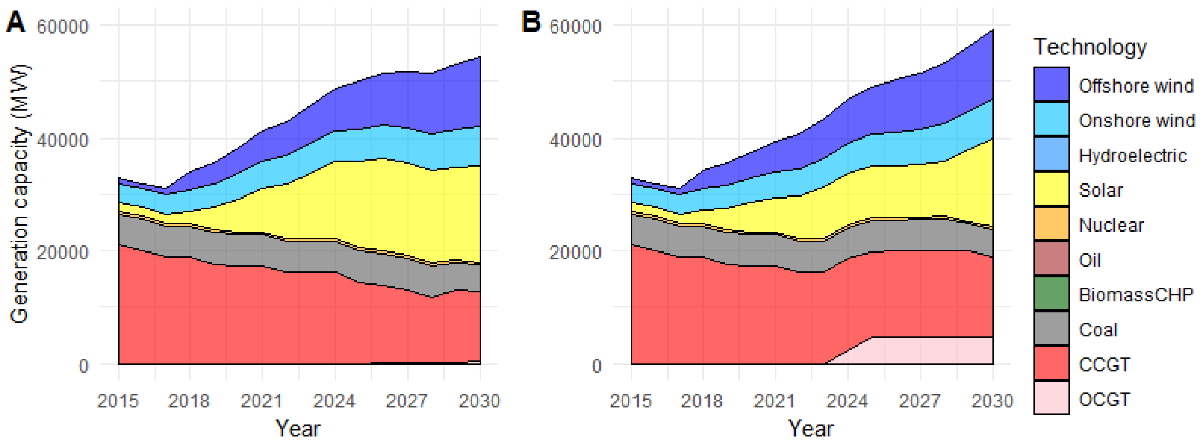

Figure 20. EMLab analysis of the NEV with increased natural gas prices.

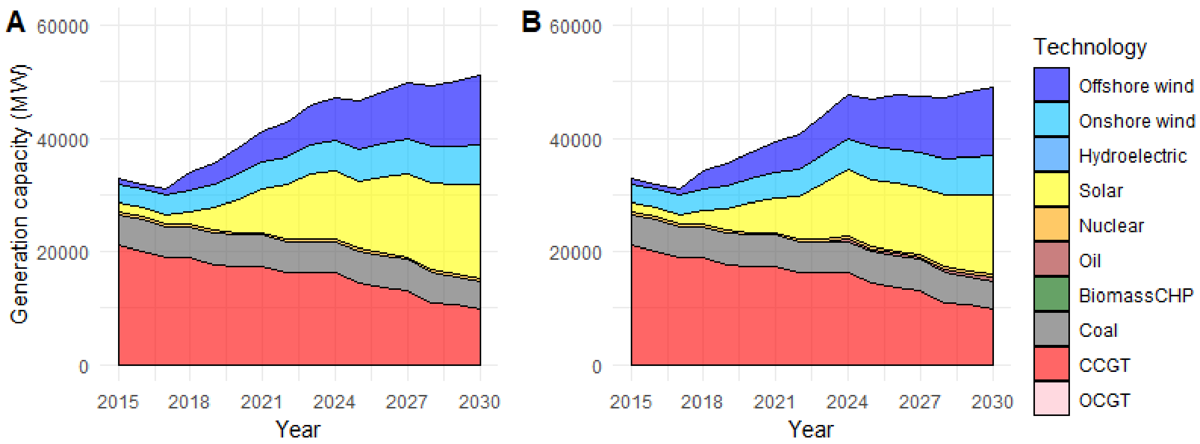

Figure 21. EMLab analysis of the NEV with no gas investments.

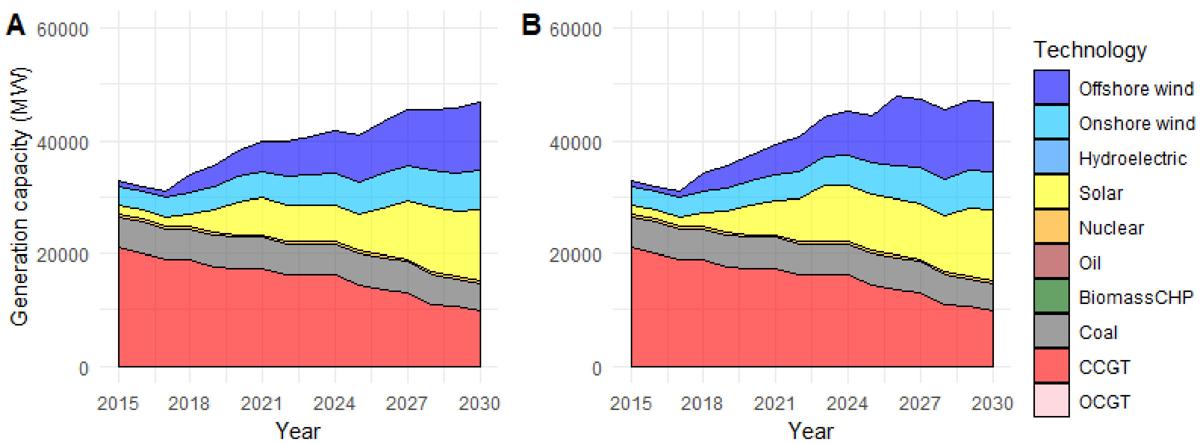

Figure 22. EMLab analysis of the NEV with similar capacity in 2030.

Figures 19, 20, 21 and 22 showed that the capital costs of solar energy were very relevant for the energy mix in 2030. In order to explore the relationship, figure 23 was constructed. Figure 23 displays the results for a constant demand while the other parameters, except for the capital costs of solar, were adjusted to the NEV estimates. The relation between the price of installing new solar capacity and the final installed capacity in 2030 for solar, OCGT, and CCGT can be seen. For prices between 0.33 €/W and 0.45 €/W, the amount of installed solar capacity in 2030 changes greatly depending on the price. Furthermore, for higher amounts of solar installed solar capacity in 2030, more OCGT is installed and less CCGT. The blue horizontal line displays the NEV estimate for solar capacity in 2030.

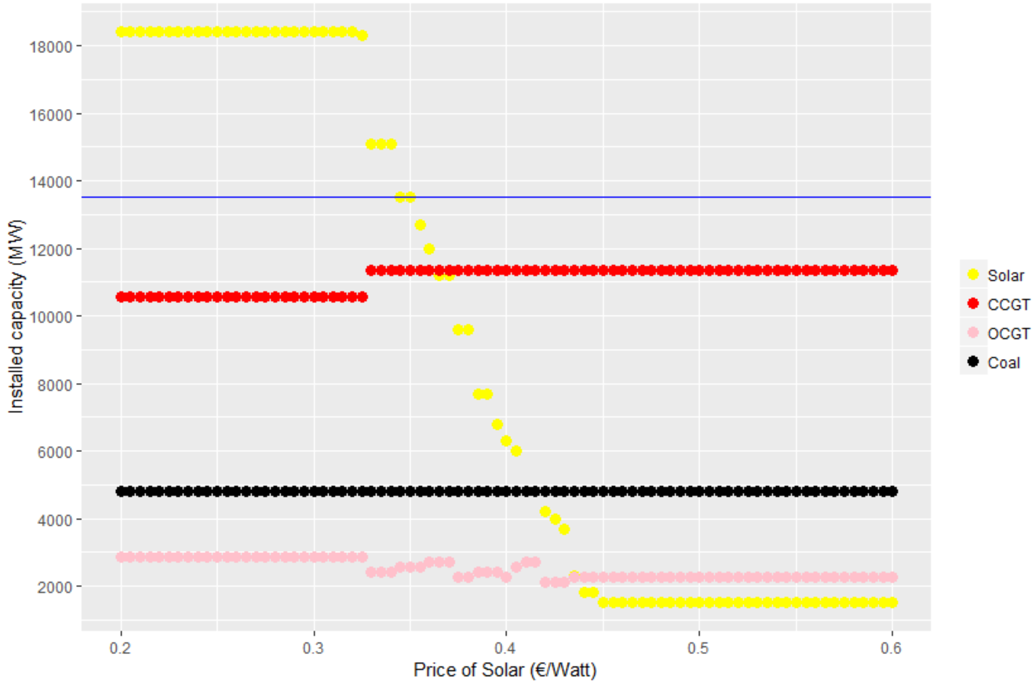

Figure 23. Relation between the price of solar and the energy mix in 2030 for a constant demand.

Figure 24. was constructed by using the NEV parameters, except that the demand was changed to the increased demand. Compared to figure 23, notable differences are that firstly, the amount of installed OCGT and especially CCGT in 2030, regardless of the price of constructing solar capacity, is much higher when there is an increase in demand than when there is a constant demand. Secondly, the slope of the installed solar capacity in 2030 for the increased demand is much less steep compared to the price of solar for the constant demand. Thirdly, the increase and decrease in OCGT and CCGT installed capacity in 2030 occurs at higher solar prices for an increase in demand than for the constant demand.

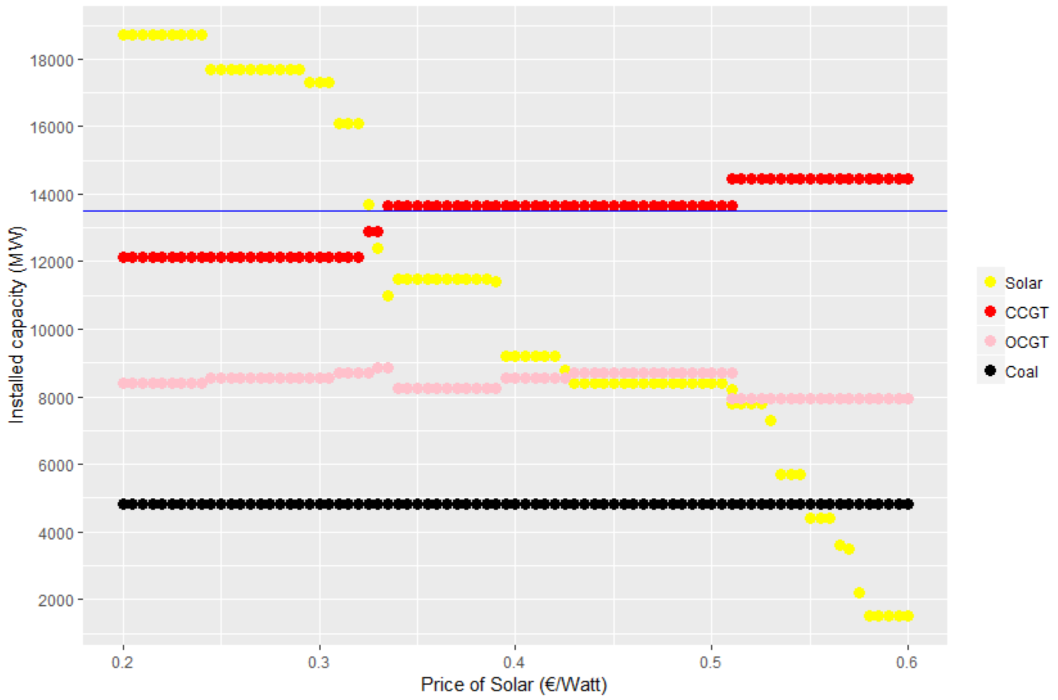

Figure 24. Relation between the price of solar and the energy mix in 2030 for an increased demand.

Table 7. The installed capacity in 2030 in MW for each figure.

Figure	16. NEV capacity estimates	18a. Initial EMLab analysis	18b. Initial EMLab analysis	19a. Similar solar capacity	19b. Similar solar capacity	20a. Increased gas prices	20b. Increased gas prices	21a. No gas investments	21b. No gas investments	22a. Conform NEV estimates	22b. Conform NEV estimates
Hydroelectric	0	0	0	0	0	0	0	0	0	0	0
Onshore wind	7000	6994	6994	6994	6994	6994	6994	6994	6995	6994	6930
Offshore wind	12000	12256	12256	12256	12256	12256	12256	12256	12256	12256	12256
Solar	14000	1500	1500	13500	13700	17000	15600	16800	8280	12600	12600
Nuclear	510	485	485	485	485	485	485	485	485	485	485
Oil	0	0	0	0	0	0	0	0	0	0	0
OCGT	N/A	2250	7950	2550	8700	600	4650	0	0	0	0
CCGT	N/A	11347	14447	11347	12897	12122	14447	9797	9797	9797	9797
BiomassCHP	0	0	0	0	0	0	0	0	0	0	0
Coal	4000	4811	4811	4811	4811	4811	4811	4811	4811	4810.8	4811
Natural gas	10500	13597	22397	13897	21597	12722	19097	9797	9797	9797	9797
Total	48010	39643	48443	51943	59843	54268	59243	51143	42625	46943	46879

5.1.2 Production

Figure 25. displays the electricity generated results of EMLab when the NEV inputs are used similarly to figure 9. Compared to the NEV estimates in figure 17 the main difference is that in the EMLab results, almost no electricity is produced from solar energy Figure 27 displays the electricity generation in 2030 when gas prices are doubled compared to the NEV estimates in 2030. Figure 28 displays the electricity generation in 2030 when no new gas capacity can be constructed between 2015 and 2030. Slightly more electricity is produced by gas in figure 27 than in figure 28, but there are no major differences between these figures. In figure 19 the electricity production is displayed for when natural gas investments are prohibited. In figure 29 the electricity production is displayed when the installed capacity in 2030 is conform to the NEV estimates.

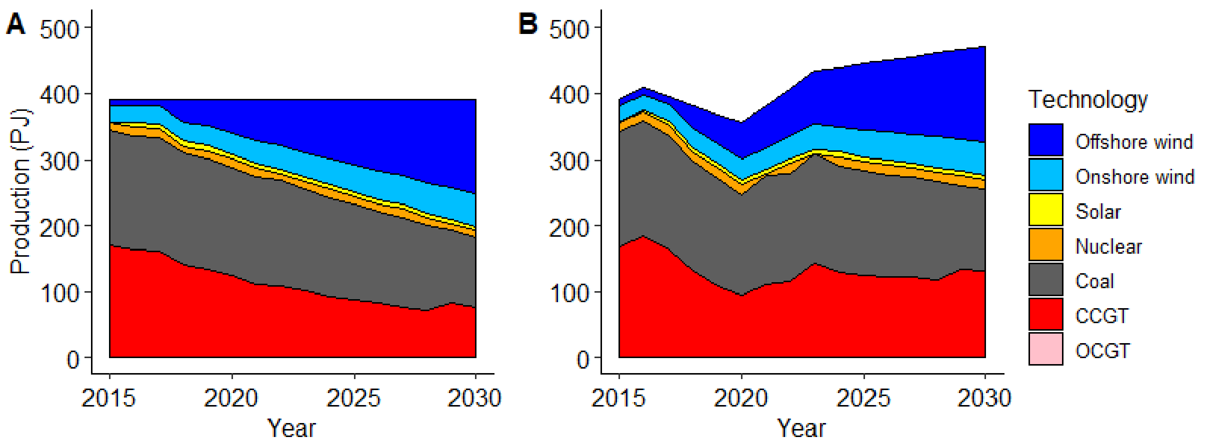

Figure 25. Initial EMLab analysis of the NEV for the production.

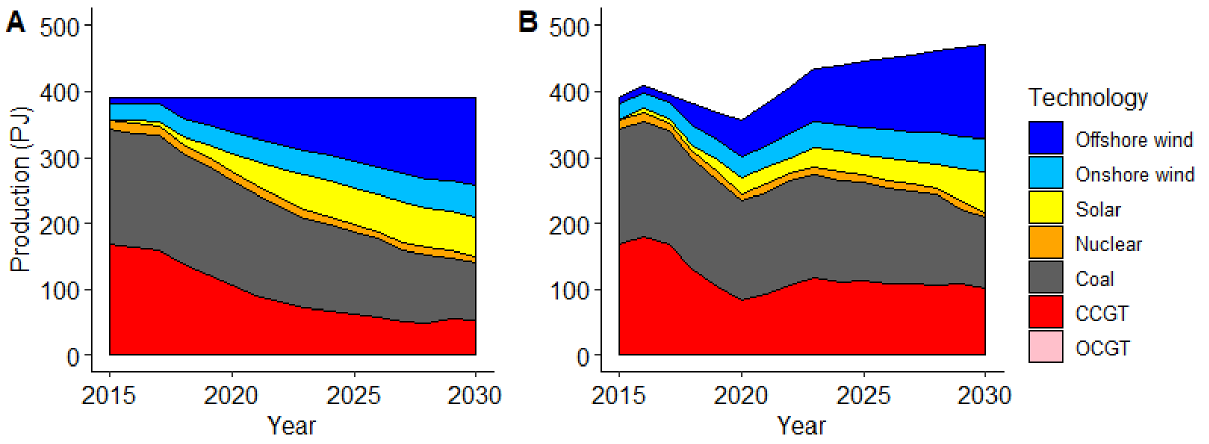

Figure 26. EMLab analysis of the NEV for the production for similar solar capacity in 2030.

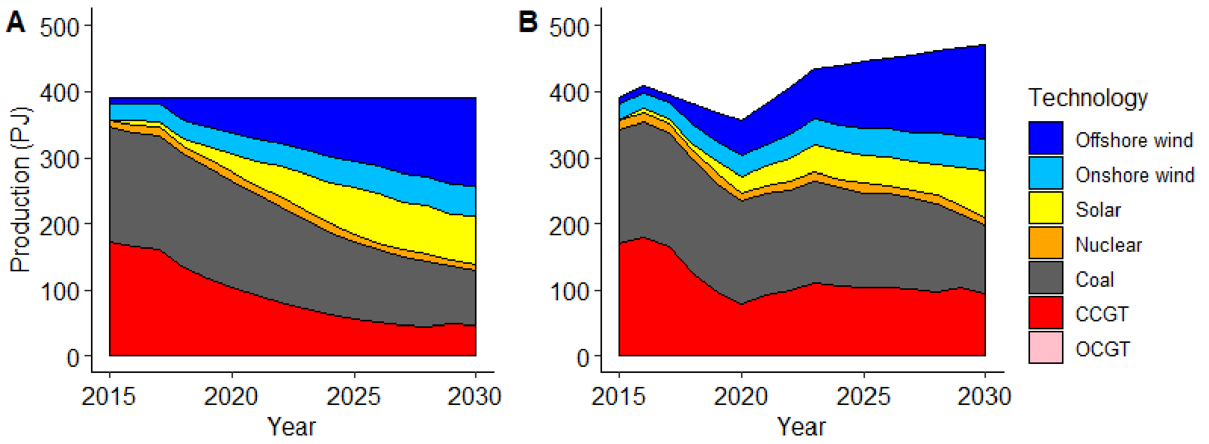

Figure 27. EMLab analysis of the NEV for the production with increased natural gas prices.

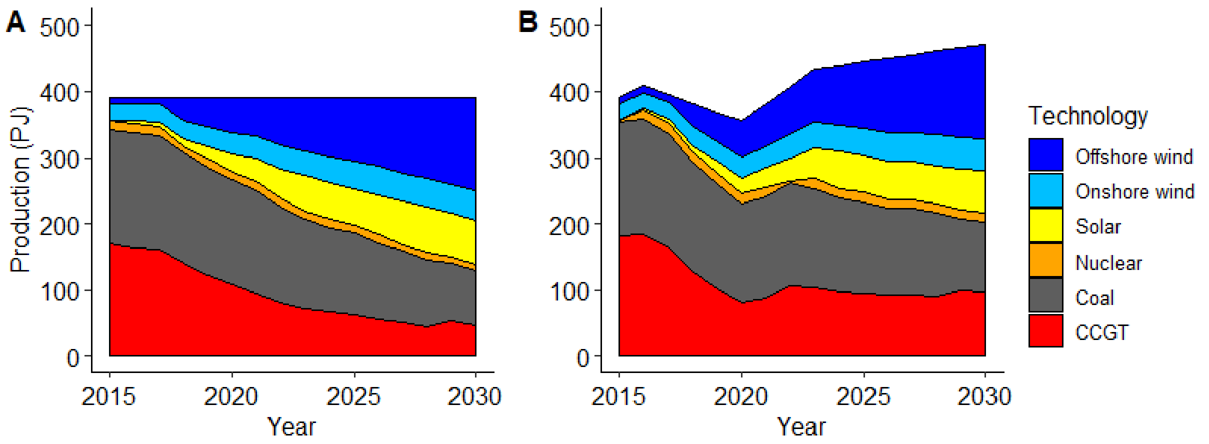

Figure 28. EMLab analysis of the NEV for the production with no gas investments.

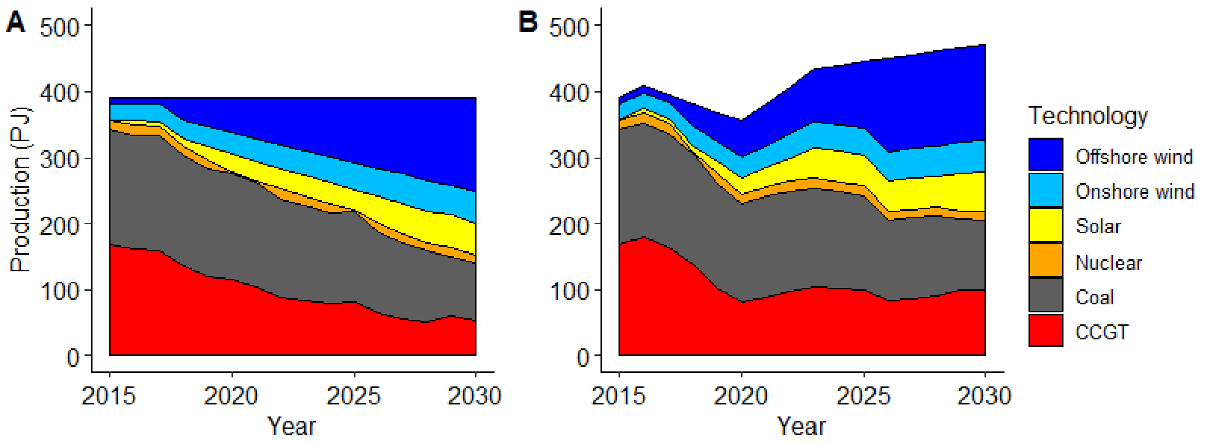

Figure 29. EMLab analysis of the NEV for the production with similar capacity in 2030.

Table 8. The production in 2030 in PJ for each figure.

Figure	17. NEV production estimates	25a. Initial EMLab analysis	25b. Initial EMLab analysis	26a. Similar solar capacity	26b. Similar solar capacity	27a. Increased gas prices	27b. Increased gas prices	28a. No gas investments	28b. No gas investments	29a. Conform NEV estimates	29b. Conform NEV estimates
CCGT	N/A	77.7	131.1	52.8	102.0	46.8	94.6	47.5	113.5	53.2	99.3
OCGT	N/A	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0
Natural gas	47.4	77.8	131.1	52.8	102.1	46.8	94.6	47.5	113.5	53.2	99.3
Offshore wind	N/A	143.0	144.6	134.9	143.4	134.3	142.8	139.8	143.6	142.5	143.9
Onshore wind	N/A	49.5	50.8	47.8	49.9	46.2	49.6	46.5	50.2	48.2	48.3
Wind	242.3	192.5	195.3	182.7	193.3	180.5	192.3	186.3	193.7	190.7	192.2
Solar	49.9	6.4	7.1	59.4	61.8	72.0	69.5	67.2	37.9	49.8	58.7
Coal	83	104.7	123.6	87.7	106.9	81.9	103.0	82.3	113.7	87.2	106.8
Nuclear	14.8	10.4	15.0	9.3	8.0	10.6	12.6	8.5	9.7	11	13
Extra	26.5	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
BiomassCHP	14.4	0	0	0	0	0	0	0	N/A	0	0
Total	478.3	391.8	472.1	391.8	472.1	391.8	472.1	391.8	468.6	391.8	470

5.1.3 Electricity prices

For reference, in figure 30 the projected electricity price of the NEV is displayed.

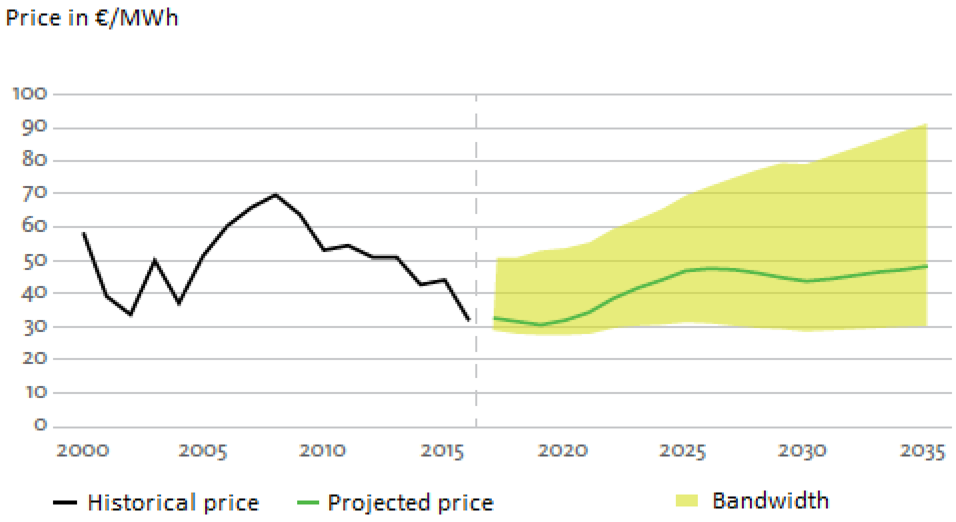

Figure 30. NEV electricity price estimates (Schoots et al., 2017, p.126).

Figure 31 displays the electricity price of figure 18. In figure 31a, 14% of the year the electricity prices would be 0 €/kWh due to the abundance of wind energy that is available. No hours exist where the VOLL is reached, and the average price is 41 euros. In figure 31b the demand is higher compared to figure 31a. This leads to a higher average price, more hours where the prices are higher, and fewer hours where the price is 0 euros.

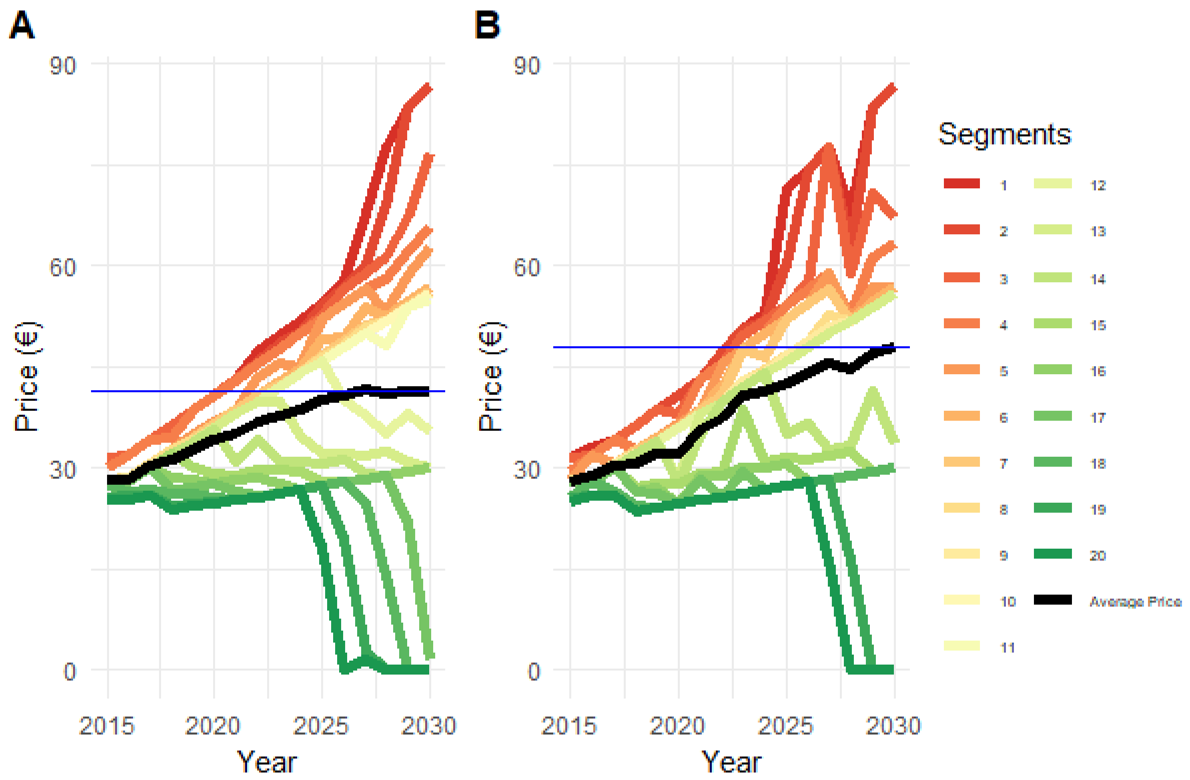

Figure 31. Initial EMLab analysis of the NEV for the electricity prices.

In figure 32 the solar capacity in 2030 was conform to the NEV estimates. Compared to figure 31, on average prices are lower and more hours have prices of 0 €/MWh. The number of hours where the price is 0 €/MWh changes from 14% in figure 31a to 20% in figure 32a, due more than 10GW additional solar capacity in 2030. Figure 32a shows a constant average price after 2023, while in figure 31a this can be seen after 2026. Similarly, to the previous comparison, figure 32b has lower average prices and more hours where the price is 0 €/MWh compared to figure 31b. The average price in 31b keeps increasing due to the additional demand. In figure 32b the average price in 2030 is lower compared to 2026, 2027, 2028 and 2029.

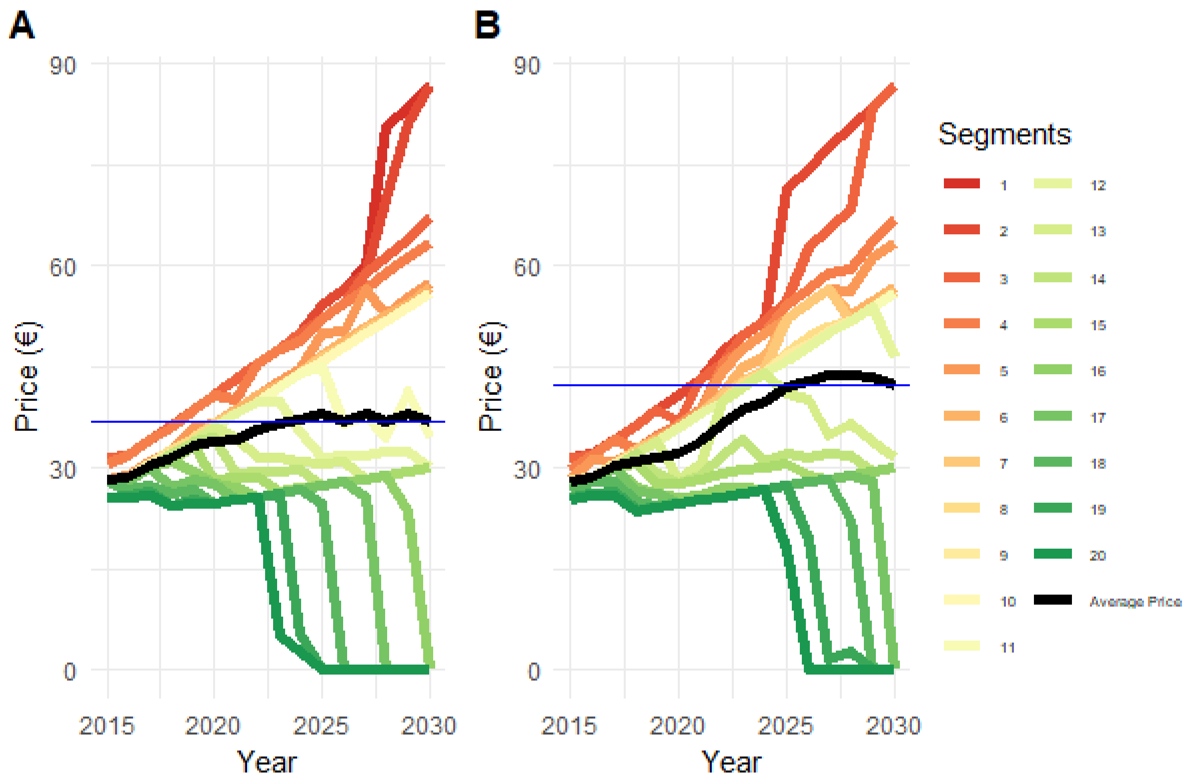

Figure 32. EMLab analysis of the NEV for the electricity prices for similar solar capacity in 2030.

Figure 33 displays the electricity prices for when the EMLab results for 2030 for the installed capacity are identical to the NEV estimates. In figure 33 the VOLL was reached and, in order to improve visibility, the VOLL was set to €300 for the graph. However, to calculate the average price the value of €2000 was still used. For the constant demand, after 2023 the average price is almost constant. Some shortages occur at 2030, but these are only happening in segment 1 and 2, which combined are only 0.1% of the total year. Therefore, the average price is not very much influenced by the hours where there are shortages. For the non-constant demand, almost 8% of the year shortages occur. This means that the additional demand is unable to be met by the installed capacity in 2030.

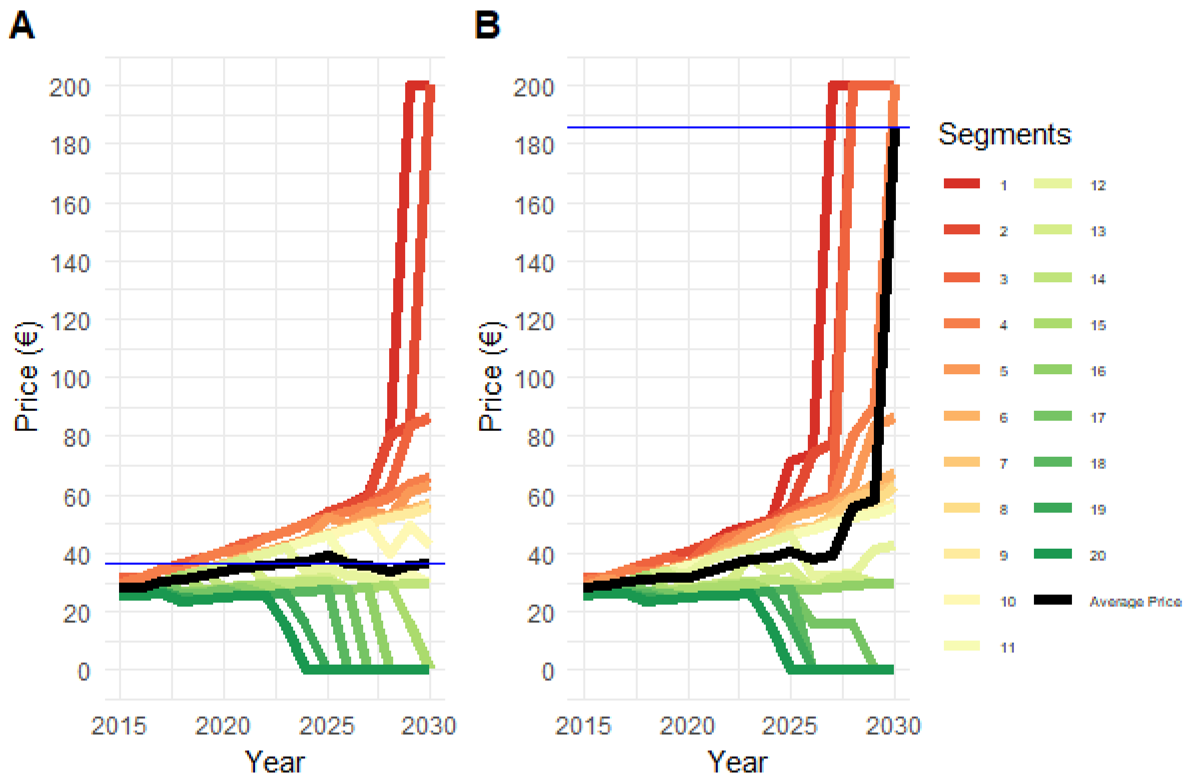

Figure 33. EMLab analysis of the NEV for electricity prices with similar capacity in 2030.

5.2 KA-act

This section shows the EMLab analysis of the KA-act estimates. The input parameters from the KA-act were used as inputs for EMLab. This means that the installed capacity in 2015, the fossil fuel and CO_2 prices, capital costs, and O&M costs from the KA-act were used. Then, if the final installed capacity in 2030 in the EMLab results was not similar to the KA-act estimate for 2030, these inputs were changed. Additionally, the projected closure of coal power plants was also mirrored in EMLab. A summary of the values of the installed capacity in 2030 can be seen in table 9 and for the production in table 10 at the end of the chapter.

5.2.1 Installed capacity

In figure 34 the KA-act installed capacity is displayed. Only values for 2030 were provided and therefore, from 2015 till 2030 the values were interpolated. However, for coal the specific roadmap as planned by the Dutch government for closing these powerplants was used. This means that in 2020 one specific plant must be closed, in 2024 another, and in 2030 the remaining. Compared to the NEV, the main differences are the additional installed solar capacity in 2030, the complete disappearance of coal power plants, and additional gas capacity in 2030. The wind energy and nuclear estimates are similar for the NEV and for the KA-act.

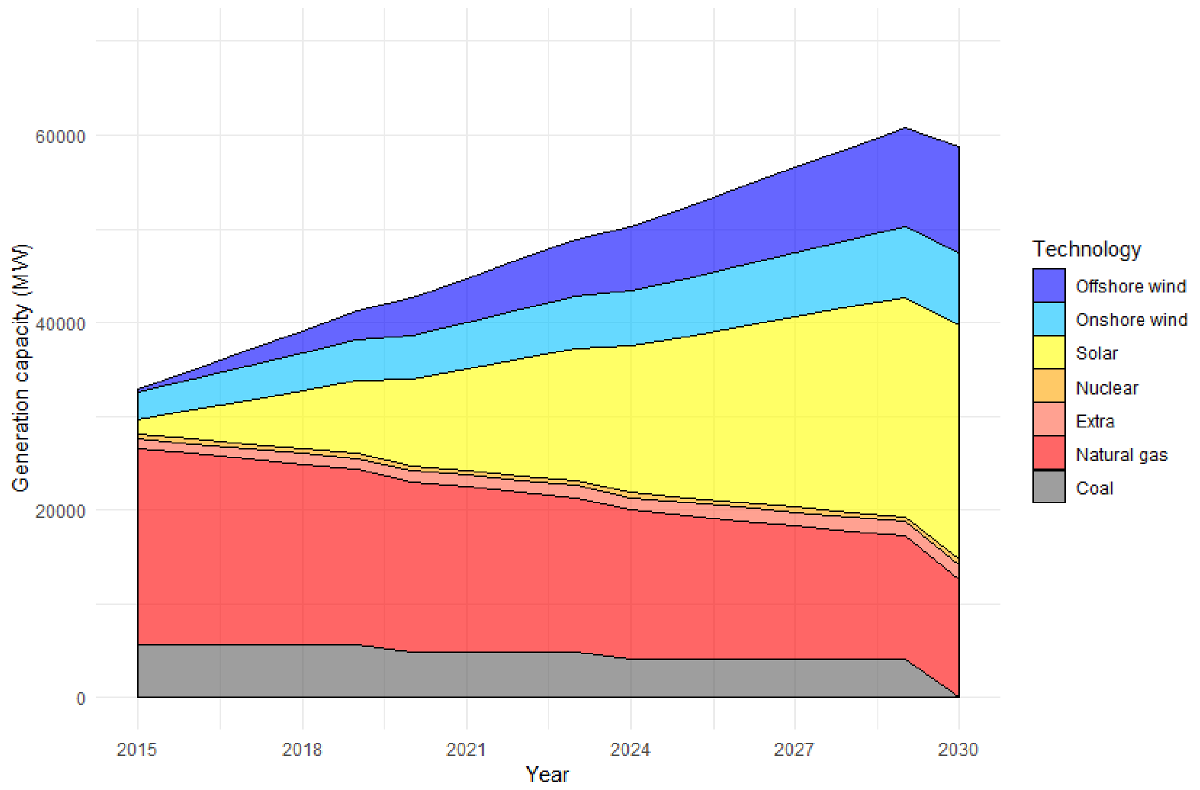

Figure 34. KA-act estimates for the installed capacity.

In figure 35 the KA-act estimates for the origin of electricity production are displayed. Similarly, to figure 25, only values for 2030 were available. The reduction in coal being used for electricity in 2020, 2024, and 2030 is caused by the phasing-out of coal.

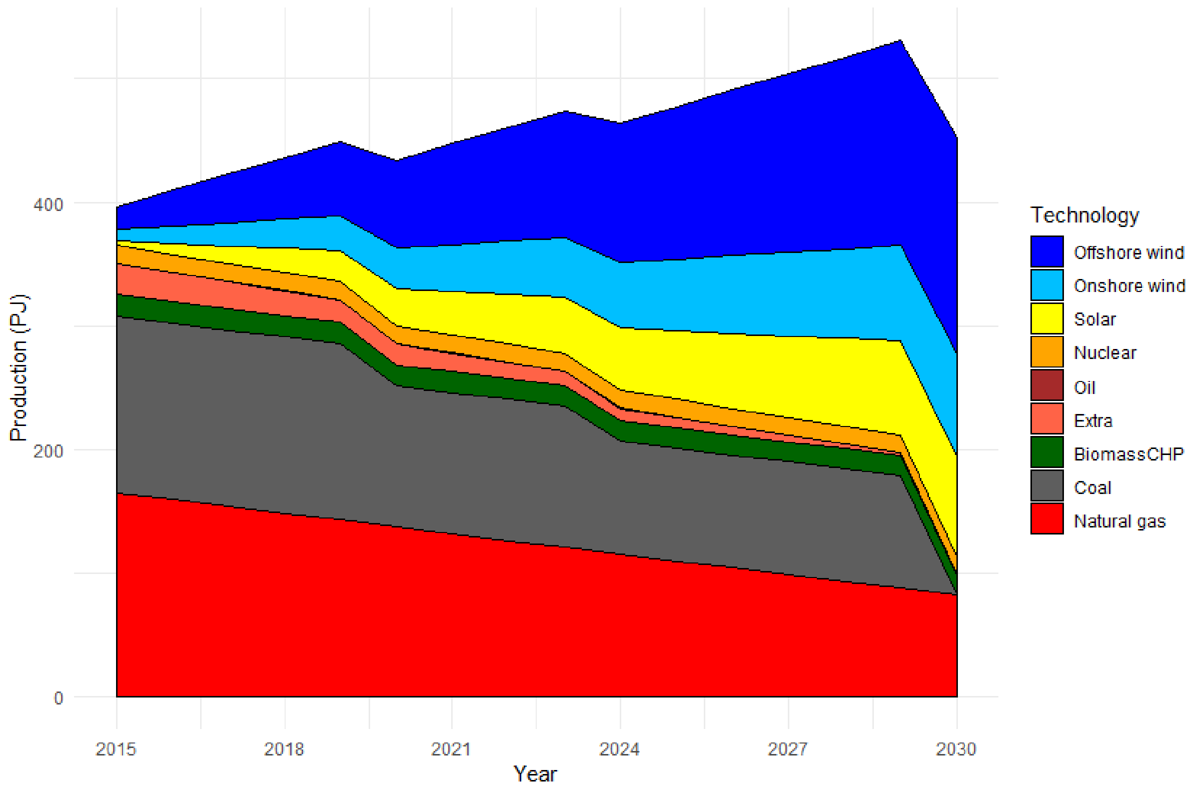

Figure 35. KA-act estimates for the production.

The KA-act specifies which monetary values for renewables are used and these were used to plot figure 36. This means that the installed capacity in 2015, the capital and O&M costs, and the fossil fuel and CO2 prices from the KA-act were used as input for EMLab. However, for solar energy additional SDE+ subsidies are present in the KA-act per delivered kwh, which were not used for figure 27. Figure 36 shows that without these subsidies, no investments in solar energy are made and that therefore the total installed capacity in 2030 in the EMLab analysis is almost 20GW lower than for the KA-act estimates. The EMLab analysis also projects a much greater amount of natural gas installed capacity to be present in 2030. Especially for figure 36b, the amount of additional commissioned natural gas capacity increases greatly once the total demand starts to increase.

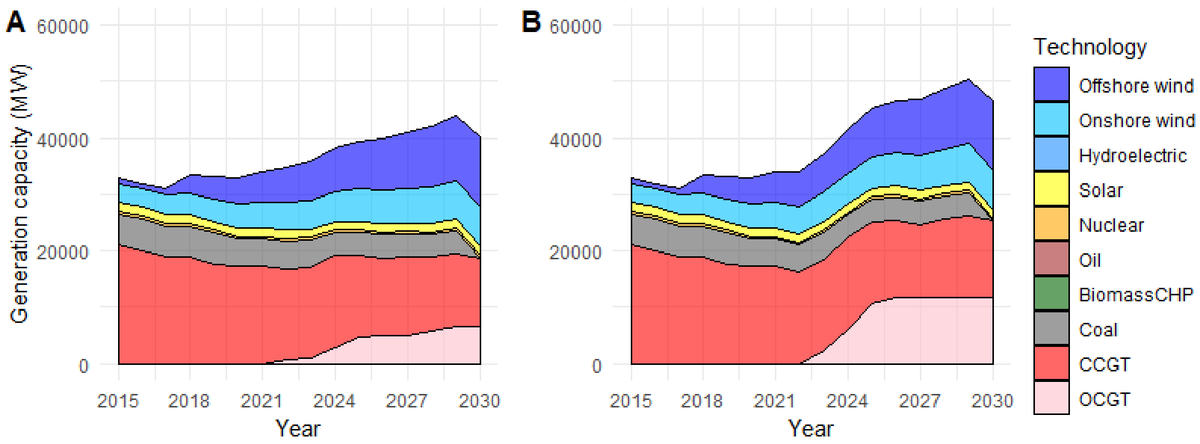

Figure 36. Initial EMLab analysis of the KA-act for the installed capacity.

For figure 37, the KA-act prices for solar energy were used, but this time SDE+ values for providing solar energy were used. Assuming standard test conditions and 2.8 equivalent sunshine hours in the Netherlands, this would lead to 0.16 €/W (Lensink, 2019). Still too much natural gas capacity is present in 2030 compared to the KA-act estimates and the solar capacity in 2030 is not conform to the KA-act estimates.

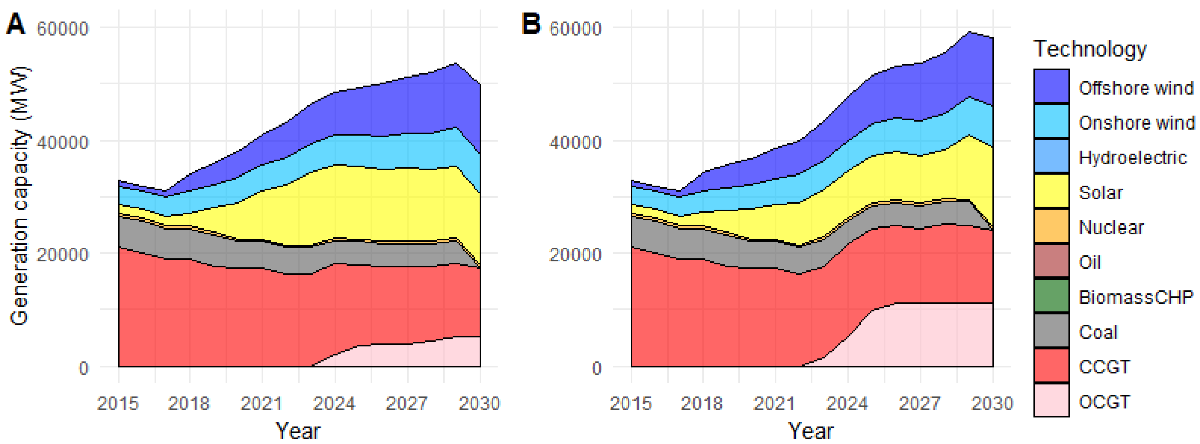

Figure 37. EMLab analysis of the KA-act for the installed capacity for 0.16 €/W solar capital costs.

Figure 38 displays the installed capacity in the EMLab analysis of the KA-act when the solar capacity in 2030 is similar to the KA-act estimates. This was obtained by using the target investor in EMLab to construct an additional 11.6 GW of solar capacity. Figure 38 shows that still too much natural gas is commissioned by the energy producers compared to the KA-act estimates for 2030.

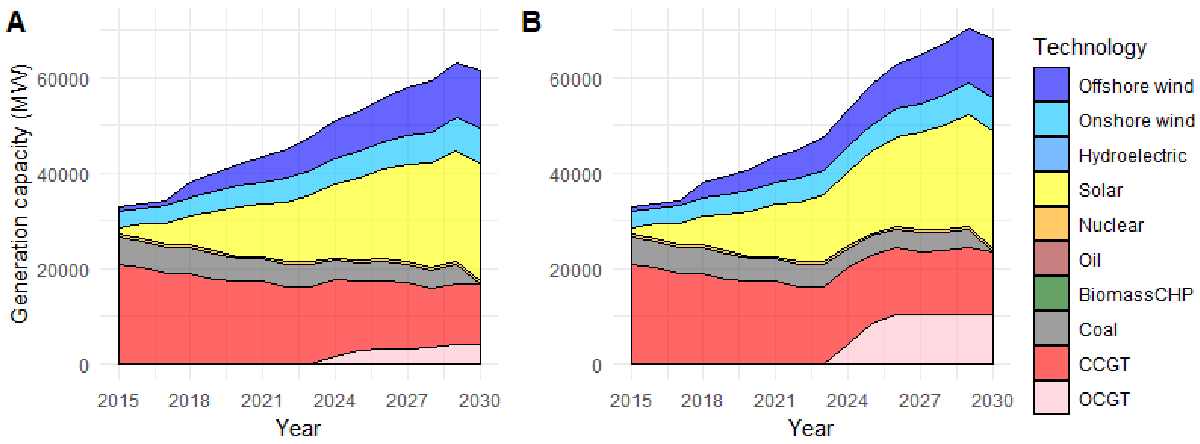

Figure 38. EMLab analysis of the KA-act for similar solar capacity in 2030.

Figure 39 shows the installed capacity of the EMLab analysis of the KA-when the capital costs of natural gas investments are increased to extremely high values. This was done in order to ensure that the estimates for 2030 for the EMLab analysis are like the KA-act estimates. In figure 39 therefore the values that are displayed are similar to the KA-act estimates for 2030.

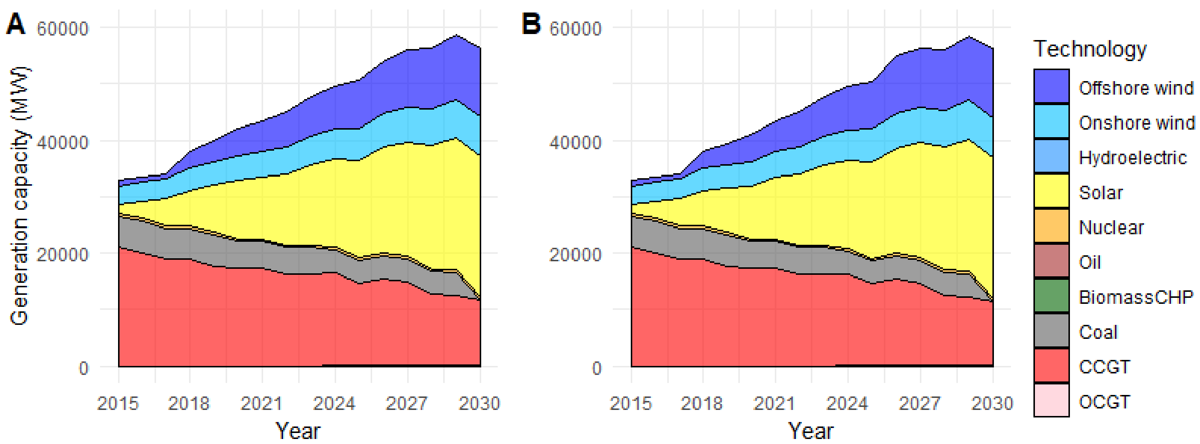

Figure 39. EMLab analysis of the KA-act for the installed capacity conform KA-act estimates.

Table 9. The installed capacity in 2030 in MW for each figure.

Figure	34. KA-act capacity estimates	36a. Initial KA-act analysis	36b. Initial KA-act analysis	37a. Similar solar capacity	37b. Similar solar capacity	38a. Increased gas prices	38b. Increased gas prices	39a. No gas investments	39b. No gas investments
Hydroelectric	0	0	0	0	0	0	0	0	0
Onshore wind	7800	7800	7800	7800	7800	7800	7800	7800	7800
Offshore wind	11300	11500	11500	11500	11500	11500	11500	11500	11500
Solar	25000	1500	1570	13400	15900	24990	24990	24990	24990
Nuclear	510	485	485	485	485	485	485	485	485
Oil	0	0	0	0	0	0	0	0	0
OCGT	N/A	6675	11700	0	300	3900	10500	300	150
CCGT	N/A	12122	13595	12122	12297	12897	12897	11347	11347
Natural gas	12600	18797	25295	12122	12597	16797	23397	11647	11497
BiomassCHP	1600	0	0	0	0	0	0	0	0
Coal	0	0	0	0	0	0	0	0	0
Extra	1600	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Total	58812	40082	46650	45307	48282	61522	68122	56422	56272

5.2.2 Production

In figures 40 till 43, respectively the productions of figures 36 till 39 are displayed. All figures show a sharp increase in the usage of natural gas to produce electricity in 2030 due to the disappearance of coal. Furthermore, some figures show that for years where there is a short spike in the usage of natural gas, before coal is phased out, nuclear energy as a fuel source is displaced. Almost no electricity is produced by OCGT plants.

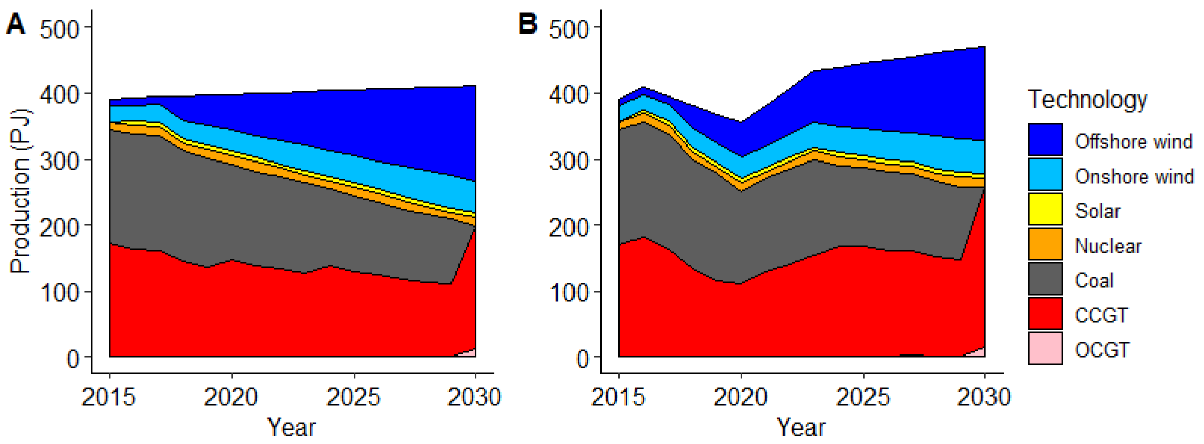

Figure 40. Initial EMLab analysis of the KA-act for the production.

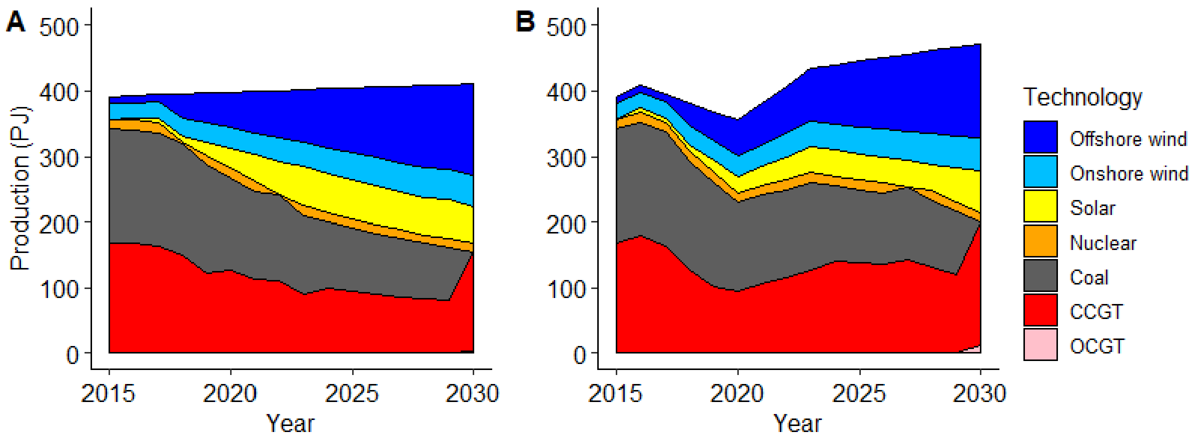

Figure 41. EMLab analysis of the KA-act for the production with 0.16 €/W solar capital costs.

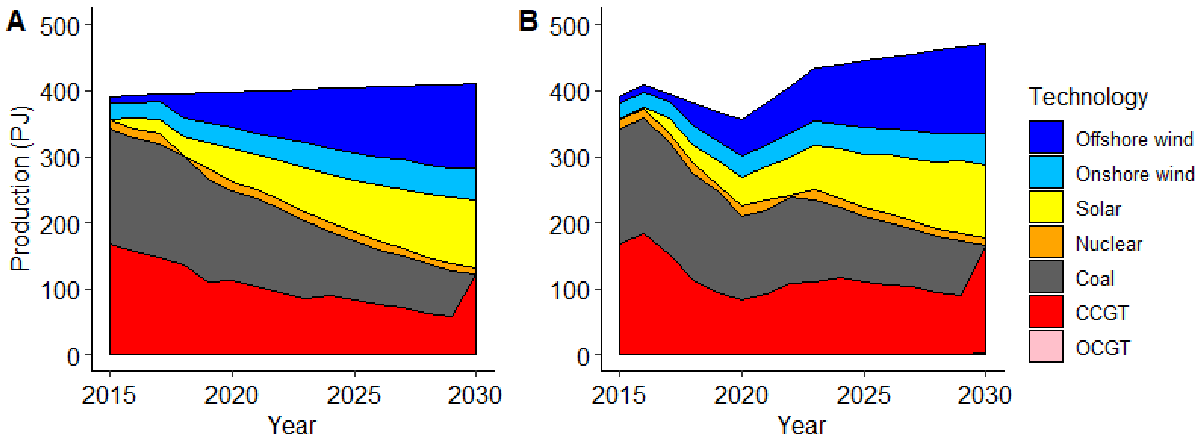

Figure 42. EMLab analysis of the KA-act for production with similar solar capacity in 2030.

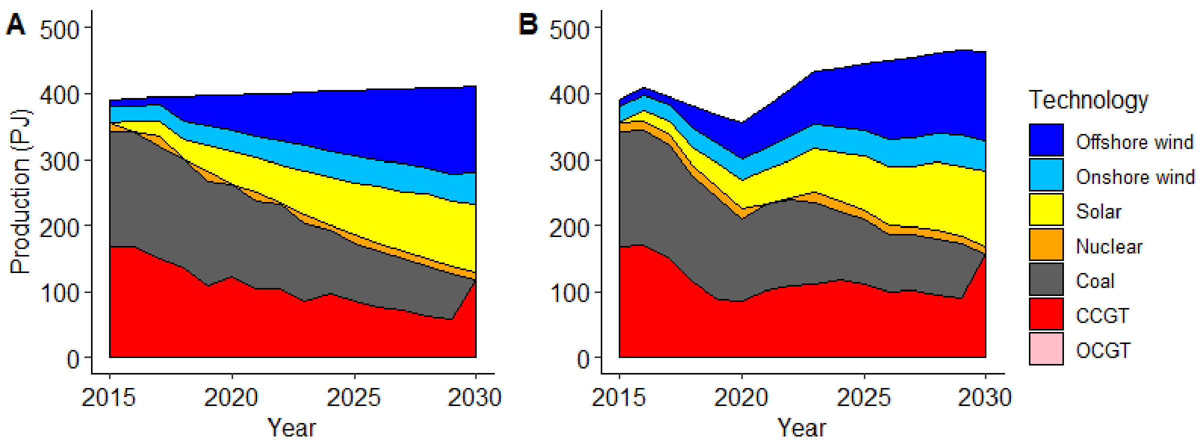

Figure 43. EMLab analysis of the KA-act for the production with capacity in 2030.

Table 10. The production in 2030 in PJ for each figure.

Figure	35. KA-act capacity estimates	40a. Initial KA-act analysis	40b. Initial KA-act analysis	41a. Similar solar capacity	41b. Similar solar capacity	42a. Increased gas prices	42b. Increased gas prices	43a. No gas investments	43b. No gas investments
CCGT	N/A	186.7	242.1	160.2	210.5	121.2	162.6	117.9	156.4
OCGT	N/A	11.6	14.5	7.6	19.6	0.2	3.9	0.4	0.6
Natural gas	82.4	198.4	256.7	167.8	230.1	121.4	166.6	118.3	157.1
Offshore wind	175.7	143.7	142.2	142.9	144.5	129.0	136.1	131.0	135.0
Onshore wind	82.4	50.0	50.8	46.9	50.4	47.4	49.0	47.0	45.7
Wind	258.1	193.7	193.0	189.8	194.9	176.4	185.1	178.0	180.6
Solar	81.7	7.1	7.4	53.5	33.2	104.0	109.4	105.0	115.8
Coal	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Nuclear	14.0	12.5	15.0	0.5	14.0	9.8	11.0	10.0	11.0
Extra	0.4	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Biomass CHP	15.8	0	0	0	0	0	0	0	0
Total	452.5	411.6	472.1	411.6	472.1	411.6	472.1	411.3	464.5

5.2.3 Electricity prices

In figure 44 the price in €/MWh is displayed for the EMLab analysis of the KA-act with a similar solar capacity in 2030. No hours exist where the VOLL is reached. An increase in the average price can be noticed when the coal is removed in 2030.

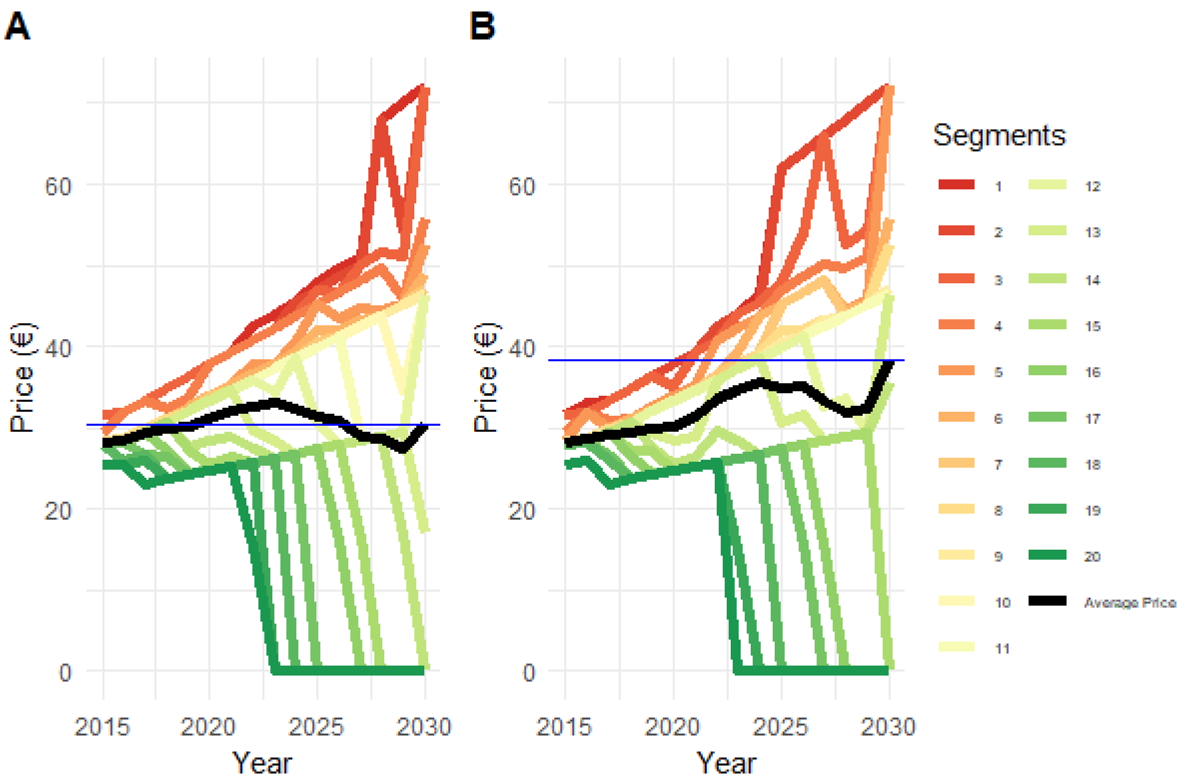

Figure 44. EMLab analysis of the KA-act for the electricity prices for similar solar capacity in 2030.

For figure 45 the composition of the total installed capacity in 2030 was equalized in EMLab compared to the KA-act. For visualisation purposes, the VOLL was displayed as 330 €/MWh. The KA-act estimates the average price to be between 50 and 52 €/MWh, while the EMlab outcome for the estimated demand has an average price of 47 €/MWh. Figure 45b displays the electricity prices for when the demand is increased. It shows that in the EMLab analysis, this outcome will lead to many hours of shortages. These shortages will cause the average price to increase to 310 €/MWh due to the fact that for 14% of the year, the VOLL will be reached. This only occurs in 2030, when the coal power plants have been decommissioned. There are still more than 20% hours in 2030 where the price is 0 according to figure 45a and 13% hours for figure 45b.

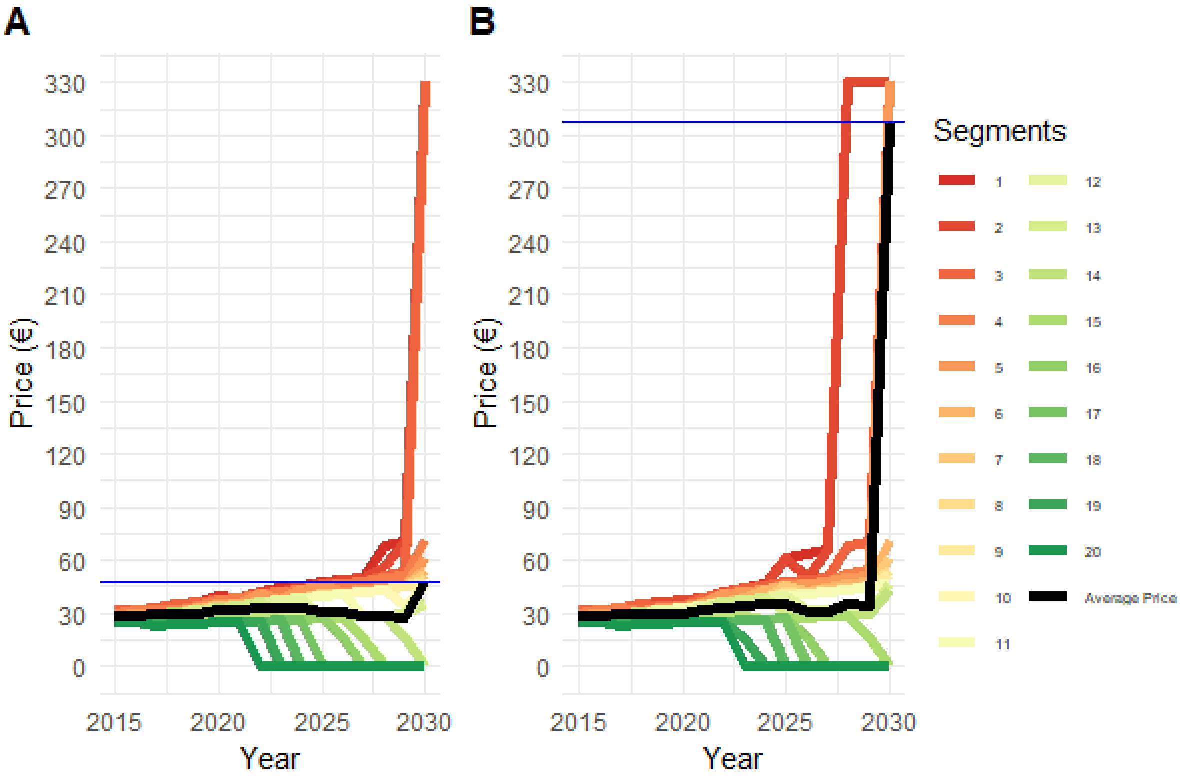

Figure 45. EMLab analysis of the KA-act for the electricity prices with similar capacity in 2030.

6. Discussion

This section will first discuss the dissection of the scenarios and if ABM was used in the construction of any of the scenarios. Then, it will discuss how the results of the EMLab analysis compare to the scenario estimates of the NEV and the KA-act and what these differences mean for the role of ABM in scenario development. For each scenario a table will be displayed with the outcomes of the ABM analysis. Then, the measures that had to be used in order to reach those outcomes will be discussed and linked to the differences between ABM and the scenarios.

6.1 Scenario classification

The dissection of the scenarios and the concluding synthesis showed that ABM is currently not used to construct energy scenarios for the Netherlands. This does not mean that the importance of behaviour is ignored in the scenarios. Generally, the concept of behaviour is present in many of the scenarios either implicitly or explicitly. Two distinctive methods for the calculation/projection of investments in the scenarios can be identified. First, in a very simplified description, there is assumed to be one system planner that invests in additional capacity once the profitability of this technology reaches a certain level. A multitude of other factors could impact this investment, such as the perceived maximum that can be invested at once, the amount of capacity that can exist, and the competition with other technologies. This method corresponds to the method used by optimisation models as defined by ……Second, the simulation models explore how a specific future can be obtained, or what possible futures can exist.

The first method is standard for optimisation models as stated in the literature. This means that optimisation models are used to construct many of the scenarios analysed in this research. The scenarios which are explorative and predictive all use optimisation models. The limitations that this method has for modelling behaviour are mentioned by all these scenarios. The scenario owners acknowledge either the need for behaviour to be explored more in-depth, or state how it limits the results. The scenarios which use the second method also do not model behaviour with the usage of an agent-based model. Similarly, these scenarios also state the importance of behaviour.

6.2 ABM analysis

6.2.1 ABM analysis of NEV

6.2.1.1 NEV Constant demand

In table 11 the results of the ABM analysis have been combined into a comparison to the estimates of the NEV scenario. For each variable it has been indicated whether the ABM analysis outcome was similar, similar after policy intervention (SPI), similar after financial adjustment (SFA), or different. One column represents the comparison between the EMLab analysis for the constant demand, while the other column represents the comparison between the EMLab analysis for the increased demand.

Table 11. Summary of ABM analysis of the NEV compared to NEV estimates.

NEV estimates	Constant demand	Increased demand
Installed solar capacity in 2030	Similar	Similar
Installed wind capacity in 2030	Similar	Similar
Installed coal capacity in 2030	Similar	Similar
Installed natural gas capacity in 2030	SPI	SPI
Average electricity price in 2030	Similar	Different
Maximum electricity price in 2030	Different	Different
Minimum electricity price in 2030	Different	Different

The constant demand analysis shows that without any solar SDE+ subsidies the outcome of the EMLab analysis for installed capacity is not similar to the NEV estimates for 2030 (figure 16 and figure 18a). For the wind power capacity in 2030, the results are similar. This is because wind power projects until 2030 are already planned by the Dutch government and the energy companies in EMLab do not invest into additional wind power on top of these planned investments. For coal both the NEV estimates and the EMLab analysis reach the same value in 2030.

For solar power, no investments are made in the EMLab analysis when solar capital costs from the literature are used. However, with current subsidy estimates for solar energy, EMLab reaches similar values as the NEV for installed solar power in 2030 (figure 19a) (Lensink, 2019). As was shown in figure 23, the amount of solar capacity in 2030 can change greatly throughout a certain price range. It is unlikely that the price of solar will be exactly so that the results of the NEV are reached through EMLab, but if the NEV would have data on this relation as well, these results could be compared in order to obtain more insights in how imperfect information can reduce the competitiveness of solar energy.

In the EMLab analysis, more gas is commissioned than is estimated by the NEV. This is because current Dutch CCGT plants are decommissioned after reaching the age of 40, which is their expected lifetime. In order to compensate for this decommissioning, the energy producers in the EMLab analysis invest in additional fossil fuel capacity. Thereby, it seems that the additional renewable capacity is unable to prevent these investments into natural gas (figure 19a). Even when the price of natural gas is doubled compared to WEO estimates, the total natural gas capacity in 2030 is still higher than the NEV estimates (figure 20a). This means that the energy companies in EMLab expect investments in natural gas to be more profitable than the NEV expects. Only when natural gas investments are prohibited, are the NEV estimates reached in EMLab (figure 21).

When the installed capacity in 2030 in EMLab is conform to the NEV estimates for 2030, the electricity price that EMLab calculated is an average price of 37 €/MWh in 2030 (figure 33a). The NEV projects a price of 43 €/MWh for 2030 with a bandwidth between 30 €/MWh and 80 €/MWh in 2030. Furthermore, the NEV contains interconnections with other countries while the version of EMLab used for this research does not. Interconnectivity can increase or decrease the average electricity price in a country and the effect depends on a variety of factors. For example, the Netherlands will be an exporting country in 2030 according to the NEV, which means that interconnectivity could increase the average price for the Netherlands (Di Cosmo, Bertsch, & Deane, 2016). This is because prices in other countries will be higher than Dutch prices. Therefore, the average price in the Netherlands will increase because the Dutch market will balance out with the higher priced neighbouring markets (Di Cosmo et al., 2016). The presence of interconnectivity in the NEV, combined with the expectation that the Netherlands will be an electricity exporting country could therefore explain the difference in the average electricity price in the NEV estimates compared to the EMLab results. Furthermore, the EMLab result is in the bandwidth of the NEV estimates and therefore it can be concluded that the EMLab analysis reaches similar outcomes as the NEV estimated electricity prices.

6.2.1.2 NEV Increased demand

For the analysis in which the demand was increased, similar results as in the constant demand analysis can be seen. Installed wind and coal capacity are the same as the NEV estimates, while no investments are made in solar power without any additional subsides. Additionally, in the increased demand even more investments in natural gas are made than in the constant demand (figure 18).

Compared to the constant demand analysis, the effect of the price of solar on the installed solar capacity in 2030 is more gradual in the increased demand analysis (figure 23 and figure 24). At an electricity price of 0.325 €/W, the amount of installed solar energy in 2030 is similar to the NEV estimate, which is a lower solar price than in the constant demand analysis. This could be caused by the fact that more CCGT and OCGT capacity is installed when the demand is increased, which causes solar energy to become a less preferable. These additional investment in natural gas are similar to the NEV constant demand analysis, except they are amplified for the increased demand analysis

Figures 25, 26, 27, and 28 show that when a lot of OCGT capacity is installed, almost no electricity is generated by OCGT power plants. As defined in the literature, OCGT plants have low capital costs and high marginal costs compared to CCGT plants (Rahman, Ibrahim, Taib, Noor, & Bakar, 2010). The reason why the energy companies in EMLab would choose to invest in OCGT power plants instead of CCGT plants is therefore that they assume hours of shortage to occur as OCGT plants are able to recover their costs during peak hours. However, when looking at figures 31 and 32, no shortages occur as the price for €h in 2030 never reaches the VOLL. The fact that a lot of OCGT capacity is installed, almost no electricity is produced by OCGT, and that there are no hours where the electricity price reaches the VOLL shows that the investments in OCGT were not optimal. The investment costs could be recovered in later years, but that also means they could have been commissioned later. This is an example of non-optimal investment behaviour. The energy producers foresaw shortages appearing in the market due to the decommissioning of old power plants and invested accordingly. However, these shortages occurred not often enough and therefore their investments in hindsight can be defined as sub-optimal.

Once the installed capacity in 2030 for the increased demand analysis is conform the NEV estimates, the EMLab price results are much higher than the NEV estimates (figure 33b). The reason for this difference is since the VOLL is reached for many hours of 2030 in the increased demand analysis. This great difference in the average price shows that certain policy interventions might lead to very different consequences if the demand changes. For the constant demand, a ban on natural gas investments made sure the EMLab results were conform the NEV estimates and did not cause high electricity prices. However, if demand increases while natural gas investments are banned, very high electricity prices will occur. Interconnectivity might be a solution to mitigate the impacts of these shortages, but it still means that the Netherlands would have to rely on neighbouring countries in order to prevent price spikes for electricity if demand increases.

6.2.1.3 NEV Shared insights

The NEV analysis with EMLab shows that the results of the NEV are replicable in EMLab with investment costs that are supported by literature. Additionally, the electricity production and prices are very similar between both approach and differences in average prices can be explained by the literature. However, in EMLab more gas investments are made than in the NEV. These investments are made because the energy producers in EMLab do not have perfect foresight. An additional benefit of ABM can be found when comparing the electricity prices in 2030 between the NEV estimates, the constant demand, and the increased demand. Influencing behaviour can stop overinvestments by energy producers and lead to a desired outcome. However, these interventions can also become counter-productive once demand increases.

6.2.2 ABM analysis of KA-act

In table 12 the results of the ABM analysis have been combined into a comparison with the estimates of the KA-act scenario. For each variable it has been indicated whether the ABM analysis outcome was similar), similar after policy intervention (SPI), similar after financial adjustment (SFA), or different. One column represents the comparison between the EMLab analysis for the estimated demand analysis, while the other column represents the comparison between the EMLab analysis for the increased demand analysis.

Table 12. Summary of ABM analysis of the KA-act compared to KA-act estimates.

KA-act estimates	Estimated demand	Increased demand
Installed solar capacity in 2030	Different	Different
Installed wind capacity in 2030	Similar	Similar
Installed coal capacity in 2030	Similar	Similar
Installed natural gas capacity in 2030	SPI	SPI
Average electricity price in 2030	Similar	Different
Maximum electricity price in 2030	Different	Different
Minimum electricity price in 2030	Different	Different

6.2.2.1 Estimated demand

The EMLab analysis of the KA-act does not reach the KA-act estimates for 2030 without any renewable subsidies for solar (figure 34 and figure 36a). Installed wind capacity in 2030 is the same as no additional investments are made. In the EMLab analysis of the KA-act even more natural gas capacity is installed compared to the EMLab analysis of the NEV. The KA-act does estimate a natural capacity in 2030 of 12.6 GW, the NEV estimates 10.5 GW, and the EMLab analysis of the KA-act reaches 19 GW in 2030.

The installed capacity of solar in the KA-act estimates for 2030 is 25 GW. This value was not reached either by reducing the price of solar to the price as found for the EMLab analysis of the NEV (0.35 €/W), or by reducing the price to the SDE+ price as defined in the results (figure 37a and figure 38a). This shows that EMLab is unable to reach the KA-act estimates the solar capacity in 2030 when solar prices are used that are supported by the literature or by the KA-act itself. This means that additional subsidies would have to be used for solar power. In the KA-act, the PV modules of households are also contributing to the 25 GW in 2030. Because EMLab does not contain household agents, these PV modules are not present. When the price of solar energy in EMLab is set to the SDE+ subsidies, 13.4 GW is installed in 2030. This would mean that 11.6 GW PV modules would be needed.

In order to still reach the solar estimates of the KA-act in 2030 with EMLab, the target investor was used to add the additional 11.6 GW of solar capacity. However, this additional solar capacity only reduces OCGT investments slightly and the EMLab results of the KA for natural gas capacity in 2030 are still higher than the KA-act (figure 38a). Since a complete ban on investments in natural gas would cause the capacity of the EMLab analysis of the KA-act in 2030 to be too low, the price of natural gas investments was adjusted in such a way that EMLab would reach the same values as the KA-act estimates. This was done by increasing the capital costs of natural gas plants to extremely high values. These values will not occur in reality and therefore another measure would have to be taken to limit the investment in natural gas. One example of this could be to place a ceiling on new investments in fossil fuel technologies. It can be concluded that the energy companies according to the EMLab analysis, invest more in natural gas than estimated in the KA-act.

The EMLab analysis of the KA-act indicates that energy producers would invest more in natural gas capacity than is estimated by the KA-act itself. This is because the phasing out of coal power plants triggers an investment signal in reliable technologies. Even if the total installed renewable capacity in EMLab in 2030 is the same as in the KA-act estimates, these investments into natural gas still occur. The large increase in installed renewable capacity between 2015 and 2030 therefore is not enough to replace fossil investments.

When the installed capacity in the EMLab analysis of the KA-act is the same as the installed capacity in the KA-act estimates, the average electricity price in the KA-act is estimated between 50 €/MWh and 56 €/MWh while the EMLab analysis has an average price of 49 €/MWh (figure 45a). As discussed previously, this difference is most likely caused by the lack of interconnectivity in this version of EMLab. The KA-act does indicate that the highest price for electricity is estimated to be 80 €/MWh while in the EMLab analysis of the KA-act, the VOLL is reached for several hours of the year (figure 45a). However, only for 10 hours in a year the VOLL is reached and therefore this has no significant effect on the average price.

When energy producers are not limited in their investments into natural gas power plants, the same situation occurs as in the EMLab analysis of the NEV. No hours are present where the VOLL is reached, but still investments into OCGT are conducted (figure 44a). For this situation the highest price that is reached is 73 €/MWh and only limited amounts of electricity is produced by OCGT (figure 42a). When the natural gas capacity in 2030 is the same as the KA-act estimate, VOLL hours are reached. Just as for the EMLab NEV analysis, the investments into OCGT are not profitable in the time period that is used for this research.

6.2.2.2 KA-act increased demand

When the demand was further increased in the EMLab analysis of the KA-act, all the previously identified phenomena are amplified. Without any solar subsidies, no solar power is installed. No additional investments are made in wind energy except for the already planned projects. Compared to the Estimated demand EMLab analysis, even more natural gas capacity is installed. Especially the amount of OCGT capacity increases.

In order to reach a solar installed capacity of 25GW in 2030, the target investor also had to be used for the increased demand analysis. Once solar capacity is increased it reduces the amount of natural gas investments. However, still much more natural gas capacity is present in 2030. The EMLab analysis of the KA-act with increased demand has higher average electricity prices, fewer hours where the price is 0 € and more hours with high prices. The main difference between these two EMLab analyses is that in the increased demand analysis, the average electricity price in 2030 is much higher than for the regular Estimated demand if the natural gas capacity is similar to the KA-act estimate (figure 45b). However, when no restrictions are placed on investments into natural gas, the difference is much smaller (figure 44b).

6.2.2.3 KA-act shared insights

It can be concluded that the EMLab analysis of the KA-act is unable to replicate the KA-act estimates for installed capacity in 2030. Firstly, the target investor is needed to add an additional 11.6 GW solar capacity in 2030. Secondly, investments in natural gas are either too high, or too low when they are prohibited. The reason why the EMLab analysis of the KA-act has a higher installed natural gas capacity in 2030 compared to the KA-act estimates is most likely because the energy producers in EMLab foresee the coal power plants being decommissioned in the future. This causes the available capacity in the market to decrease, and together with a slight increase in demand triggers the investment in natural gas. Even when the installed solar capacity is conform the KA-act estimates, it seems the energy producers in EMLab still invest in order to profit during peak hours. Thirdly, it is impossible to achieve the KA-act estimates for natural gas in EMLab without increasing the price of investments into natural gas to extremely high values.

6.3 Role of ABM

The fact that EMLab can reach the NEV estimates for 2030 with the same starting conditions as the NEV, while also showing how uncertainty can influence investment decisions, supports the notion in the literature that ABM is able to provide new insights for modelling the energy sector (Chappin & Dijkema, 2008; Farmer & Foley, 2009; Hansen et al., 2019; Van Notten et al., 2003). The EMLab analysis of the NEV has shown that when the future would develop as indicated in the NEV, sub-optimal investments occur. EMLab predicts overcapacity in the Dutch electricity sector after 2025, while the NEV mentions that the current situation of overcapacity will disappear after 2020. This contrasting outcome is explainable because outcomes of optimisation models do not contain overinvestments because the investing actor has all information available.

Despite that the EMLab analysis of the KA-act was unable to reach the KA-act estimates in 2030 without inflating the numbers, it still shows how ABM can support scenario development. EMLab is unable to reach the estimated installed solar capacity of the KA-act in 2030. This shows that there is a maximum of solar capacity that energy companies deem to be profitable in the Dutch market. Additionally, the same overinvestments are made in the EMLab analysis of the KA-act as in the EMLab analysis of the NEV. Additionally, the decommissioning of coal power plants provides an even further incentive for the energy producers in EMLab to invest in other stabilizing energy technologies.

This ABM analysis has shown that certain investment signals, such as a decreasing available supply of reliable generation technologies, could incentivize energy producers to invest beyond what appears financially recoverable in the long run. History has shown that overcapacity is hard to predict, but still very present in European markets (Özdemir et al., 2013). The current situation in the Netherlands, where an overcapacity of installed generation exist due to the recent construction of new coal power plants, shows how important it is to try to both predict but also mitigate the impact of uncertain behaviour (Van Dril, 2017). Current energy scenarios do not include options to model the impact of uncertain behaviour. The ABM analysis in this research has shown that when an ABM is used alongside other models, it can provide new insights. For the development of future scenarios, the inclusion of ABM would improve the research on possible occurrences of overcapacity and highlight how behaviour might influence the sector.

The other benefits of ABM, representation of reality, flexibility, and cost-effectiveness as defined in Bonabeau (2002) and Bzaghandi (2012) were not explored and require a different research approach. Options to explore these benefits will be discussed in the future research section.

6.4 Limitations

This research contains several limitations. Firstly, even though the foundation for the classification of scenarios was based on literature, the actual classification is open to different interpretations. Scenarios can be large documents with a lot of information. The scenarios here were classified based on my own interpretation of the contents of these scenarios. Other researchers could have a different opinion and classify some scenarios in different categories. Secondly, the experiments which were ran in EMLab were conducted according to the topics of interest of the author. The usage of a 15% demand increase for the NEV was based on the estimated production in 2030, however an increase of 15% for electricity demand was never mentioned by the NEV. Therefore, another percentage could also have been used instead of the 15% increase. Thirdly, for parameters such as the capital costs of natural gas in EMLab which were not defined in the scenarios, data from Richstein et al. (2014) was used. More recent data will not change the outcome that overinvestments might occur as this was tested for, but it might still impact the composition of the energy mix (Richstein et al., 2014). Fourthly, the conclusion made in this research that overinvestments could occur based on the estimates from the NEV and the KA-act if uncertain behaviour is incorporated is entirely based on the assumptions and uncertainties defined in this research. Reality is much more complex and for example a financial crisis might influence the investment behaviour of companies. Finally, several modelling choices were made. These modelling choices influenced the results and were based on the assumptions of the researcher. These assumptions were:

- Using time segments in order to simulate the intermittency of renewables.
- No interconnectivity with neighbouring countries.
- The assumptions that all wind energy as planned till 2030 will be installed.
- Fossil fuels are always available.
- EMLab contains learning curves for the efficiency of investment costs and efficiency of power plants based on the WEO 2011 New Policies Scenario.

6.5 Societal and academic relevance

Scenarios have a prominent role in the Netherlands in preparing for the future. The recent calculations of the climate agreement have been extensively reported on in the news. Furthermore, the Nationale Energie Verkenning is the cornerstone for many other scenarios. As already mentioned in this research, unpreparedness can lead to financial losses and a less secure energy supply. The energy sector is also transitioning to a more sustainable sector in order to reduce the GHG emissions of the Netherlands. Therefore, although scenarios are not able to precisely estimate the future, they can assist in reducing uncertainties should be aimed for.

Exploring how behaviour might influence the energy sector in the future, can help society to understand the role behaviour can play as well as assist policy, explore options to mitigate or influence this behaviour. Although the identified investment behaviour of this research should not be interpreted as definite truths, it can show new insights that are not obtainable by traditional optimisation models. Incorporating ABM next to optimisation models can thus provide more accurate scenarios and make policy makers more prepared for the future.

6.6 Academic relevance

This study created an overview of contemporary Dutch energy scenarios for 2030 based on characteristics as defined in the literature. This overview adds to current research on energy scenarios in general as well as for the Netherlands specifically, as it represents an application of current academically defined scenario characteristics. For future research the table that was used to classify the scenarios (table 4) could be used both for other countries, but also for new scenarios.

Furthermore, benefits of ABM for exploring the future energy sector have been addressed since 2003 (see Van Notten et al., 2003), yet so far agent-based models were not used to develop energy scenarios for the Netherlands. This research has demonstrated some of these suggested benefits of ABM by showing how the results of an agent-based model could be compared to the results from other modelling technologies. Specifically, it has demonstrated how the agent-based model can be adjusted in order to aim for the results of the other modelling technologies. This provides a blueprint for anyone who wants to incorporate an agent-based model in their scenario development.

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7 Conclusion

The transition to an energy sector in the Netherlands which is less dependent on fossil fuels requires great changes. The Netherlands is currently reliant on fossil fuels for its electricity production, but these must be replaced by solar and wind energy. The energy sector is a complex system where changes in the energy mix for a country can lead to financial consequences. The inelastic demand for electricity, combined with the high capital costs of power plants, and the intermittent nature of renewable technologies make adequate planning for the future important. Energy scenarios are therefore used to explore different possible futures. Contemporary scenarios assume actors in the energy sector operate with perfect foresight. In reality, actors are not all-knowing and can make incorrect decisions, based on their limited knowledge. This uncertain behaviour of actors can greatly impact the composition of the future energy sector. An example of this is the current situation in the Netherlands where overcapacity is present. In order to try to predict this behaviour, agent-based models aim to explore how agents might behave. Agent-based modelling (ABM) has been proposed to develop scenarios, but no information exist on whether any of the Dutch scenarios have been developed with ABM.

This research aimed to first discover whether ABM was used to develop any of the existing Dutch energy scenarios for 2030. This was done by classifying and dissecting Dutch scenarios according to characteristics as defined in the literature. Secondly, this research aimed to explore how ABM could support scenario development. The classification of the scenarios showed that agent-based models were not used to develop any of them. Most scenarios were developed with the usage of optimisation model. The scenarios that did not use optimisation models used simulation models. All the scenarios highlighted the importance of behaviour and especially the behaviour of energy companies. However, the possibility of incorporating ABM in future scenarios was not mentioned. In order to see how ABM could provide new insights for scenario development, two scenarios were selected and analysed with an agent-based model. The inputs of the scenarios were used in an agent-based model in order to try to mimic the scenario estimates. If the inputs were initially unable to lead to the scenario estimates in the agent-based model, parameters such as the capital costs of technologies, policy interventions, or fossil fuel prices were adjusted in order to lead to the estimates. The reason why the scenario estimates were aimed for with the agent-based model was because this shows what impact uncertain behaviour has in the scenarios. Finally, the reason why a difference existed between the scenario estimates and the ABM analyses were discussed.

The ABM analysis shows that, for the first scenario, the ABM approach was able to mimic the scenario results. However, it also showed that the energy companies would invest in more natural gas capacity than estimated in the scenario. Signals in the market, where fossil fuel power plants are decommissioned due to them reaching their end-of-life, together with a constant or increase in demand, cause the energy producers to overinvest in natural gas technologies. These investments were found to be unable to become profitable and therefore they demonstrate how agents can overinvest when faced with uncertain information. An option to influence this behaviour was determined to be to prohibit any investments into natural gas technologies, as this option caused the agent-based model results to mirror the scenario estimates. However, when demand was increased this policy intervention caused great electricity shortages. This demonstrated that for some instances specific policy interventions might mitigate the impact of uncertain behaviour, but if the circumstances change these interventions might turn out to be counterproductive. For the second scenario, the same phenomenon was also present, even in an enlarged form. This was caused by the fact that the second scenario estimates that all coal power plants are decommissioned by 2030. Therefore, even more investments were done by the energy producers in natural gas technologies in this analysis.

As identified in this research, agent-based models are currently not yet used for scenario development. However, the ability of ABM to support scenario development has been demonstrated in this research. By being able to mirror scenario estimates, while also showing how uncertain information and behaviour can lead to different estimates, the relevance of modelling and understanding investment behaviour is highlighted. Therefore, based on these results a strong recommendation is given for including agent-based models in scenario developing.

7.1 Future research

Two scenarios were selected for this research in order to demonstrate how ABM can support the development of scenarios. The same analysis could be conducted for any other energy scenario. This can be a scenario for the Netherlands, but the methodology applied in this study can also be used for energy scenarios of other countries. Furthermore, a different ABM could be able to further analyse how consumer behaviour might impact the energy sector. Finally, for this research an existing agent-based model was applied to a scenario. For further research, an agent-based model could be developed specifically for a scenario. This would both remove the need for the model to be calibrated to the scenario and make sure all modelling choices for the scenario are present in the agent-based model.

Other benefits of agent-based models as stated in the literature, the flexibility of agent-based models, the ability to easily display the natural situation, and the cost-effectiveness of ABM were not explored in this research. To explore how ABM related to the models used for the development of energy scenarios for the Netherlands, future research should look compare these modelling techniques specifically for how they support scenarios.

Bibliography

Bale, C. S. E., Varga, L., & Foxon, T. J. (2015). Energy and complexity: New ways forward. Applied Energy, 138, 150–159. https://doi.org/10.1016/j.apenergy.2014.10.057

Bazghandi, A. (2012). Techniques, advantages and problems of agent based modeling for traffic simulation. International Journal of Computer Science Issues, 9(1), 115.

Beckman, J., Hertel, T., & Tyner, W. (2011). Validating energy-oriented CGE models. Energy Economics, 33(5), 799–806. https://doi.org/10.1016/j.eneco.2011.01.005

Bezdek, R. H., & Wendling, R. M. (2002). A Half Century of Long-Range Energy Forecasts: Errors Made, Lessons Learned, and Implications for Forecasting. 18.

Böhringer, C. (1998). The synthesis of bottom-up and top-down in energy policy modeling. Energy Economics, 20(3), 233–248. https://doi.org/10.1016/S0140-9883(97)00015-7

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. Proceedings of the national academy of sciences, 99(suppl 3), 7280-7287.

Börjeson, L., Höjer, M., Dreborg, K.-H., Ekvall, T., & Finnveden, G. (2006). Scenario types and techniques: Towards a user's guide. Futures, 38(7), 723–739. https://doi.org/10.1016/j.futures.2005.12.002

Bradfield, R., Wright, G., Burt, G., Cairns, G., & Van Der Heijden, K. (2005). The origins and evolution of scenario techniques in long range business planning. Futures, 37(8), 795–812. https://doi.org/10.1016/j.futures.2005.01.003

Brouwer, A. S., van den Broek, M., Zappa, W., Turkenburg, W. C., & Faaij, A. (2016). Least-cost options for integrating intermittent renewables in low-carbon power systems. Applied Energy, 161, 48–74. https://doi.org/10.1016/j.apenergy.2015.09.090

Buhanist, P. (2015). Path Dependency in the Energy Industry: The Case of Long-term Oil indexed Gas Import Contracts in Continental Europe. 5(4), 15.

Chappin, Emile J. L., & Dijkema, G. P. J. (2008). Agent-based modeling of energy infrastructure transitions. 2008 First International Conference on Infrastructure Systems and Services: Building Networks for a Brighter Future (INFRA), 1–6. https://doi.org/10.1109/INFRA.2008.5439580

Chappin, É. J. L. (2011). Simulating energy transitions. Next Generation Infrastructures Foundation.

Cornelius, P., Van de Putte, A., & Romani, M. (2005). Three Decades of Scenario Planning in Shell. California Management Review, 48(1), 92–109. https://doi.org/10.2307/41166329

Dam, K. H. van, Nikolic, I., & Lukszo, Z. (Eds.). (2013). Agent-based modelling of socio technical systems. Dordrecht ; New York: Springer.

Den Ouden, B., Lintmeijer, N., Bianchi, R., & Warnaars, J. (2018). Eindrapportage_systeemvraagstukken_en_afhankelijkheden_in_de_energietransitie_28052018_final.pdf.

Di Cosmo, V., Bertsch, V., & Deane, P. (2016). Impact of new interconnection lines on the EU electricity market. 2016 13th International Conference on the European Energy Market (EEM), 1–5. https://doi.org/10.1109/EEM.2016.7521311

DLR (2013). Scenario development with MESAP models. Retrieved from https://www.dlr.de/Portaldata/41/Resources/dokumente/institut/system/Modellbeschreibungen/DLR_Scenario_development_with_MESAP_2013.pdf

Edmonds, B. (2017). Different Modelling Purposes. In B. Edmonds & R. Meyer (Eds.), Simulating Social Complexity (pp. 39–58). https://doi.org/10.1007/978-3-319-66948-9_4

Eurostat. (2019). Renewable energy in the EU: Share of renewable energy in the EU up to 17.5% in 2017. Retrieved from https://ec.europa.eu/eurostat/documents/2995521/9571695/8-12022019-AP-EN.pdf/b7d237c1-ccea-4adc-a0ba-45e13602b428

Farmer, J. D., & Foley, D. (2009). The economy needs agent-based modelling. Nature, 460(7256), 685–686. https://doi.org/10.1038/460685a

Fleiter, T., Rehfeldt, M., Herbst, A., Elsland, R., Klingler, A.-L., Manz, P., & Eidelloth, S. (2018). A methodology for bottom-up modelling of energy transitions in the industry sector: The FORECAST model. Energy Strategy Reviews, 22, 237–254. https://doi.org/10.1016/j.esr.2018.09.005

Gadonneix, P., Nadeau, M.-J., Kim, Y. D., Birnbaum, L., Cho, H., & Choudhury, A. R. (2013). Officers of the World Energy Council. 44.

Gowrisankaran, G., Reynolds, S. S., & Samano, M. (2011). Intermittency and the Value of Renewable Energy. 58.

Hansen, P., Liu, X., & Morrison, G. M. (2019). Agent-based modelling and socio-technical energy transitions: A systematic literature review. Energy Research & Social Science, 49, 41–52. https://doi.org/10.1016/j.erss.2018.10.021

Helgesen, P. I. (2013). Top-down and Bottom-up: Combining energy system models and macroeconomic general equilibrium models. CenSES: Trondheim, Norway.

Herbst, A., Toro, F., Reitze, F., & Jochem, E. (2012). Introduction to Energy Systems Modelling. Swiss Journal of Economics and Statistics, 148(2), 111–135. https://doi.org/10.1007/BF03399363

Hobbs, B. F. (1995). Optimization methods for electric utility resource planning. European Journal of Operational Research, 83(1), 1-20.

Hourcade, J. C., Richels, R., Robinson, J., Chandler, W., Davidson, O. R., Edmonds, J., ... Tudini, A. (1996). Estimating the costs of mitigating greenhouse gases. In Bruce J.P.,

H. Lee, & E. F. Haites (Eds.), Climate change 1995. Economic and social dimensions of climate change (pp. 263-296). New York, NY: Cambridge University Press.

International Energy Agency. (2018). World energy outlook. Paris: Organisation for Economic Co-operation and Development.

Jacobsen, H. K. (1998). Integrating the bottom-up and top-down approach to energy.economy modelling: The case of Denmark. 20.

Jefferson, M., & Voudouris, V. (2011). Oil scenarios for long-term business planning: Royal Dutch Shell and generative explanation, 1960-2010. 41.

Kamiński, J., & Saługa, P. W. (2018). The cost of equity in the energy sector. Instytut Gospodarki Surowcami Mineralnymi i Energią PAN. https://doi.org/10.24425/124493

Kavgic, M., Mavrogianni, A., Mumovic, D., Summerfield, A., Stevanovic, Z., & Djurovic -Petrovic, M. (2010). A review of bottom-up building stock models for energy consumption in the residential sector. Building and Environment, 45(7), 1683–1697. https://doi.org/10.1016/j.buildenv.2010.01.021

Keles, D. (2013). Uncertainties in energy markets and their consideration in energy storage evaluation. 260.

Kraan, O., Kramer, G. J., & Nikolic, I. (2018). Investment in the future electricity system-An agent-based modelling approach. Energy, 151, 569–580. https://doi.org/10.1016/j.energy.2018.03.092

Lensink, S. M., & Cleijne, J. W. (2016). Eindadvies basisbedragen SDE+ 2017. ECN. Retrieved from https://www.rvo.nl/sites/default/files/2019/01/Eindadvies%20basisbedragen%20SDE%202019.pdf

Lijesen, M. G. (2007). The real-time price elasticity of electricity. Energy Economics, 29(2), 249–258. https://doi.org/10.1016/j.eneco.2006.08.008

Lund, H., Arler, F., Østergaard, P., Hvelplund, F., Connolly, D., Mathiesen, B., & Karnøe, P. (2017). Simulation versus Optimisation: Theoretical Positions in Energy System Modelling. Energies, 10(7), 840. https://doi.org/10.3390/en10070840

Ma, T., & Nakamori, Y. (2009). Modeling technological change in energy systems – From optimization to agent-based modeling. Energy, 34(7), 873–879. https://doi.org/10.1016/j.energy.2009.03.005

Macal, C. M., & North, M. J. (2010). Tutorial on agent-based modelling and simulation. Journal of Simulation, 4(3), 151–162. https://doi.org/10.1057/jos.2010.3

Matliare, T. (2012). OPTIMIZATION MODEL OF ENERGY MIX TAKING INTO ACCOUNT THE ENVIRONMENTAL IMPACT. 8.

McFarland, J., Reilly, J., & Herzog, H. (2002). Representing Energy Technologies in Top down Economic Models Using Bottom-up Information. 26.

Menkveld, M., Smekens, K. E. L., Tigchelaar, C., van der Welle, A. J., Stralen, J. V., Hekkenberg, M., ... & Peek, K. (2017). Achtergronddocument onzekerheidsanalyse Nationale Energieverkenning 2017.

Millett, S. M. (2003). The future of scenarios: challenges and opportunities. Strategy & Leadership, 31(2), 16-24.

Mulder, M. (2017). Energy Transition and the Electricity Market: An Exploration of an Electrifying Relationship. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2940974

Nakicenovic, N. (2000). Energy scenarios. World Energy Assessment of the United Nations.

Özdemir, Ö., de Joode, J., Koutstaal, P., & van Hout, M. (2013). Generation Capacity Investments and High Levels of Renewables. 34.

Paltsev, S. (2017). Energy scenarios: The value and limits of scenario analysis: The value and limits of energy scenario analysis. Wiley Interdisciplinary Reviews: Energy and Environment, 6(4), e242. https://doi.org/10.1002/wene.242

Peterson, G. D., Cumming, G. S., & Carpenter, S. R. (2003). Scenario Planning: A Tool for Conservation in an Uncertain World. Conservation Biology, 17(2), 358–366. https://doi.org/10.1046/j.1523-1739.2003.01491.x

Pfenninger, S., Hawkes, A., & Keirstead, J. (2014). Energy systems modeling for twenty-first century energy challenges. Renewable and Sustainable Energy Reviews, 33, 74–86. https://doi.org/10.1016/j.rser.2014.02.003

Rahman, M. M., Ibrahim, T. K., Taib, M. Y., Noor, M. M., & Bakar, R. A. (2010). Thermal Analysis of Open-Cycle Regenerator Gas-Turbine Power-Plant. 4(8), 6.

Richstein, J. C., Chappin, E. J. L., & de Vries, L. J. (2014). Cross-border electricity market effects due to price caps in an emission trading system: An agent-based approach. Energy Policy, 71, 139–158. https://doi.org/10.1016/j.enpol.2014.03.037

Rijksdienst voor Ondernemend Nederland. (2019). Windenergie op zee. Retrieved from https://www.rvo.nl/subsidies-regelingen/stimulering-duurzame energieproductie/categorie%C3%ABn/windenergie-op-zee. Accessed on 15-5-2019

Rogelj, J., den Elzen, M., Höhne, N., Fransen, T., Fekete, H., Winkler, H., … Meinshausen, M. (2016). Paris Agreement climate proposals need a boost to keep warming well below 2 °C. Nature, 534(7609), 631–639. https://doi.org/10.1038/nature18307

Rooijers, F., Schepers, B., van Gerwen, R., & Van der Veen, W. (2014). Scenario ontwikkeling energievoorziening 2030. CE Delft and DNV GL, 14, C93.

Rui, Z., Metz, P. A., Reynolds, D. B., Chen, G., & Zhou, X. (2011). Historical pipeline construction cost analysis. International Journal of Oil, Gas and Coal Technology, 4(3), 244. https://doi.org/10.1504/IJOGCT.2011.040838

Ruijven, B. J. van. (2008). Energy and development a modelling approach. Utrecht: Utrecht University, Copernicus Institute for Sustainable Development and Innovation, Department of Science, Technology and Society.

Rutte III, K. (2017). Regeerakkoord: Vertrouwen in de toekomst.

Schoemaker, P. J. H. (1995). Scenario Planning: A Tool for Strategic Thinking. SLOAN MANAGEMENT REVIEW, 17.

Schoots, K., Hekkenberg, M., & Hammingh, P. (2017), Nationale Energieverkenning 2017. ECN-O--17-018. Petten: Energieonderzoek Centrum Nederland

Simon, S., Naegler, T., & Gils, H. (2018). Transformation towards a Renewable Energy System in Brazil and Mexico—Technological and Structural Options for Latin America. Energies, 11(4), 907. https://doi.org/10.3390/en11040907

Spataru, C. (2017). Whole Energy System Dynamics. London: Routledge, https://doi.org/10.4324/9781315755809

Spruijt, J. (2015). Wat levert een Zonneweide per ha op?. ACRRES-Wageningen UR.

Streck, C., Keenlyside, P., & von Unger, M. (2016). The Paris Agreement: A New Beginning. Journal for European Environmental & Planning Law, 13(1), 3–29. https://doi.org/10.1163/18760104-01301002

Teske, S., Sawyer, S., Schäfer, O., Pregger, T., Simon, S., Naegler, T., ... & Rutovitz, J. (2015). Energy [r]evolution-a sustainable Netherlands energy outlook 2013.

Tol, R. S. (2007). The value of lost load (No. 214). ESRI Working Paper.

Van Beeck, N. M. J. P. (1999). Classification of energy models. FEW Research Memorandum. Operations research, Tilburg.

Van Dril, A. W. N. (2017). Employment effects in Dutch gas and coal fired powergeneration.

Van Hout, M., Koutstaal, P., & Özdemir, Ö. (2019). Achtergrondrapport effecten ontwerp klimaatakkoord: Elektriciteit. 28.

Van Notten, P. W. F., Rotmans, J., van Asselt, M. B. A., & Rothman, D. S. (2003). An updated scenario typology. Futures, 35(5), 423–443. https://doi.org/10.1016/S0016 3287(02)00090-3

Van Vuuren, D. P. (2007). Energy systems and climate policyâ€ ”Long-term scenarios for an uncertain future. Utrecht University.

Voß, A., Schlenzig, C., & Reuter, A. (1994). MESAP-III: a tool for energy planning and environmental management: history and new developments; STE-Seminar, KFA Jülich, 6. September 1994.

Urgenda. (2017). Nederland 100% Duurzame Energie in 2030. Retrieved from https://www.urgenda.nl/wp-content/uploads/Urgenda-Rapport-Duurzame-Energie-in -2030-v2-2017.pdf

Weeda, M., & Smekens, K. E. L. (2017). Verkenning Energievoorziening 2035.

Weijermars, R., Taylor, P., Bahn, O., Das, S. R., & Wei, Y.-M. (2012). Review of models and actors in energy mix optimization – can leader visions and decisions align with optimum model strategies for our future energy systems? Energy Strategy Reviews, 1(1), 5–18. https://doi.org/10.1016/j.esr.2011.10.001

Wilkinson, A. (2009). Scenarios practices: in search of theory. Journal of futures studies, 13(3), 107-114.

Zeng, Y., Cai, Y., Huang, G., & Dai, J. (2011). A Review on Optimization Modeling of Energy Systems Planning and GHG Emission Mitigation under Uncertainty. Energies, 4(10), 1624–1656. https://doi.org/10.3390/en4101624

Appendix. Scientific paper

Agent-based modelling in energy scenario development

An analysis of contemporary energy scenarios for the Netherlands.

Max Bosch, 4503295

Abstract - In order to determine how the energy sector of the Netherlands can or should look in the future, energy scenarios are used to explore possible alternative futures. Many scenarios for the Netherlands exist, but a classification of contemporary Dutch electricity scenarios is missing. Additionally, agent-based modelling (ABM) has often been proposed for energy scenario development as it is able to model the uncertain behaviour of energy companies, which is not possible in more traditional energy scenario models. However, a recent publication of the impacts of the Dutch climate agreement seems to suggest that agent-based modelling is not yet used to develop energy scenarios in the Netherlands. This research first classified Dutch energy scenarios for 2030 which are focused on the electricity sector. Additionally, it analysed one Dutch energy scenario with EMLab, an agent-based model. The agent-based model was able to replicate the scenario results when the inputs of that scenario were used. Additionally, it showed how uncertain behaviour would cause overinvestments and what measures can be used to impact this behaviour. The results show that ABM can and should be used to support scenario development for the Netherlands.

Keywords: agent-based modelling – energy scenario – Netherlands 2030 - electricity

Introduction

The Netherlands will have to make vast changes in its energy sector in order to meet international obligations and to reduce greenhouse gas (GHG) emissions (Regeerakoord 2017). Existing coal power plants will have to be closed and a large share of the electricity production should originate from wind and solar energy. Replacing the fossil fuel technologies by renewables can cause electricity prices to go up and electricity shortages to occur due to the intermittent nature of renewables (Gowrisankaran, Reynolds, & Samano, 2011; Lijesen, 2007). In order to mitigate the possible negative consequences of a transition to a more sustainable energy sector, scenarios can be used (Van Vuuren, 2001). Scenarios explore different pathways to the future and can be used by policy makers in order to understand the workings and possible developments of the energy sector.

Models are at the core of energy scenarios (Lund et al., 2017; Weijermars, Taylor, Bahn, Das, & Wei, 2012). Most energy scenarios use either simulation or optimisation models. Many assumptions in these models are made in order to represent the energy sector (Chappin, 2011). Especially for behaviour many assumptions are made since behaviour is very difficult to predict and to model (Bezdek & Wendling, 2002; Dam, Nikolic, & Lukszo, 2013). The ability of agent-based modelling to incorporate uncertain actor behaviour has been mentioned by multiple authors (Chappin, 2011; Farmer & Foley, 2009; Hansen, Liu, & Morrison, 2019). However, the recent calculations of the Dutch climate agreement suggest that ABM is not yet used to develop Dutch energy scenarios (Van Hout, Koutstaal, & Özdemir, 2019). In order to highlight how precisely ABM can support scenario development, this research will analyse one energy scenario with an agent-based model. However, in order to first determine how behaviour is already present in Dutch scenarios for 2030, current Dutch scenarios were dissected and classified.

A classification can both show how behaviour is currently present in the scenarios, as well as help to provide a distinction between the scenarios. Based on this classification one scenario will be selected. The inputs of each respective scenario will be used in an agent-based model and the outcomes of this model for installed capacity in 2030, the electricity production in 2030, and the electricity prices in 2030 will be compared to the scenario estimates. The differences between the ABM approach and the scenario estimates will be linked to the way each method incorporates uncertain behaviour.

Literature review

Theoretical background

Scenarios for the energy sector became prominent around 1960-1970 due to growing international uncertainties and events such as the oil crisis of 1973-1974 (Jefferson & Voudouris, 2011). This section will first determine what classifies as a scenario Secondly, it will explore methods used to distinguish different types of scenarios. Thirdly, it will address commonly used modelling techniques for electricity scenarios, such as top-down, bottom-up, narrative, and agent-based modelling techniques. Finally, it will investigate which properties are relevant in classifying energy scenarios.

As defined by Peterson et al. (2003), scenario planning is a systemic method to explore possible futures. Peterson et al. (2003) further specify that scenarios cannot accurately predict the future, and that they should not be forecasts due to the structural uncertainties of systems (Peterson, Cumming, & Carpenter, 2003). Millet (2003) highlights the fact that there are multiple different definitions of scenarios, and that this conflicting terminology hinders the usefulness of scenarios (Millet, 2003). Building onto the work of Millet, Bradfield et al. (2005) conclude that the definitions of planning, thinking, forecasting, analysis, and learning are core concepts in scenario planning, but that various interpretations exist on the role of these concepts in scenario planning and on their specific meaning (Bradfield, Wright, Burt, Cairns, & Van Der Heijden, 2005).

Different classifications

All scenarios contain assumptions in order to deal with uncertainties. Examples of uncertainties are the future electricity demand, the behaviour of actors in the sector, and on how high fossil fuel and CO2 prices will be in the future (Börjeson, Höjer, Dreborg, Ekvall, & Finnveden, 2006; Van Notten, Rotmans, van Asselt, & Rothman, 2003). In addition to these general characteristics, a distinction between different types of scenarios can be made based on other factors. Börjeson et al. (2006) concluded that although many specific types can be distinguished, in general these types can be classified as either predictive, explorative, or normative scenarios. Where predictive scenarios explore "*What will happen?"* explorative scenarios try to identify *"What can happen?"* and normative scenarios determine "*How can a specific target be reached?*"(Börjeson et al., 2006). Van Notten et al. (2003) and Nakicenovic (2000) classify scenarios as either descriptive or normative, where descriptive scenarios explore open-ended paths into the future. Normative scenarios are value-based and explore options to reach a desirable future (Nakicenovic, 2000; van Notten et al., 2003). Scenarios can also differ based on what method they use, their subject, timescale, spatial interpretation, level of deviation from the status quo, the level of integration, and what uncertainties they use. These uncertainties for electricity scenarios are fossil fuel and CO2 prices, energy demand, innovation, and policies (Börjeson et al., 2006; Keles, 2013; Peterson et al., 2003; Van Notten et al., 2003; Van Vuuren, 2001). Based on all these characteristics as defined in the literature, table 1 was constructed.

Table 1. Characteristics as found in the literature.

Component	Options
General type	Predictive Explorative Descriptive Normative
Methods	Backcasting Forecasting New methods
Subject	
Timescale	
Spatial	
Data	Qualitative Qualitative
Level of deviation	Business as Usual (BAU) Unconventional disruptions
Uncertainties:	
Method	Alternative scenario approach Probabilistic approach
Fossil fuel prices	Fossil fuel prices
CO_2 *prices*	CO_2 prices
Energy Demand	Demand
Innovation	Innovation
Policies	Policies

Modelling of scenarios

Energy scenarios rely largely on models in order to identify their results. Historically energy models can be classified in two general categories: bottom-up models and top-down models (Hourcade et al., 1996; Van Beeck, 1999). Although there are some conflicting definitions regarding the terms, bottom-up models usually contain a large amount of technical details and predict the future without looking at other sectors influencing the energy sector. Top-down models look at the energy sector from a more economic perspective, by including welfare and profit maximization, without looking at the technical properties (Beckman, Hertel, & Tyner, 2011; Böhringer, 1998; McFarland, Reilly, & Herzog, 2002). One important conclusion that Van Beeck (1999) found is that although specific types of models are usually associated with either the top-down category or the bottom-up category, this distinction is no longer always needed. For example, optimisation models are classified as bottom-up models. However, economic top-down models have started to include optimisation as well. A narrower distinction can be made for energy scenario models. Lund et al. defined two archetypes for energy scenario modelling, optimisation and simulation models (Lund et al., 2017; Pfenninger, Hawkes, & Keirstead, 2014).

Optimisation models

Optimisation models are currently often used to model the energy sector (Ma & Nakamori, 2009; Pfenninger et al., 2014; Weijermars et al., 2012; Zeng, Cai, Huang, & Dai, 2011) . At the core of optimisation models is an objective function for which an optimal solution is found (Hobbs, 1995; Ma and Nakamori, 2009). In addition optimisation models can contain many constraints, rules, and assumptions (Lund et al., 2017; Ma & Nakamori, 2009). Classic optimisation models often use a central entity who has perfect information and foresight on future changes in the system (Pfenninger et al., 2014).

Simulation models

The main difference between optimisation and simulation models according to Lund et al. (2017) is that optimisation models aim to find the optimal solution, whereas simulation models want to explore how a system will act in the future. Related to this is that Edmons (2017) states that in order to understand optimisation models, one can analyse the mathematics behind it. For simulation models this is harder because the goal of simulation models is to determine how a system will work (Edmonds, 2017).

Agent-based models

Macal and North (2010) state that typical agent-based models contain agents, interactions between these agents, and an environment. Furthermore, they state that the most important property of ABM is that agents act autonomously and are not guided (Macal & North, 2010). Contrary to classic optimisation models as defined by Pfenninger et al., one of the main differences between these approaches for the energy sector is that in traditional optimisation models, investments are made by a central planner who has perfect information (Pfenninger et al., 2014). In an agent-based model, the lack of perfect information and the autonomy of agents will therefore most likely lead to sub-optimal investments compared to the outcomes of an optimisation model.

Methodology

The research design used in this study is twofold. Firstly, the scenarios were dissected and qualitatively analysed. Secondly, these inputs and assumptions were used in an agent-based model in order to analyse the scenarios in combination with an ABM.

Data collection

To find relevant electricity scenarios for the Netherlands, an online search was conducted which looked at news articles, journal publication, and the websites of energy actors. Additionally, a publication made by Berenschot for the Dutch Ministry of Economic Affairs and Climate which conducted a literature review on existing Dutch scenarios was used to verify the selected scenarios (Den Ouden, Lintmeijer, Bianchi, & Warnaars, 2018). Five keywords were used, both in Dutch and in English: Dutch, energy, scenarios, 2030, and electricity. To expand the search, different combinations of these keywords were used in multiple search queries.

The selected scenarios are displayed in table 2. In total, nine scenarios were found. However, three scenarios were excluded because one did not contain enough information regarding the electricity sector and installed capacity for the Netherlands (by TenneT), while the others (by Natuur&Milieu and Gasunieverkenning) did not contain details for 2030 specifically.

Table 2. Overview of scenarios.

Scenario name	Abbreviation	Date of publication
Nationale Energie Verkenning	NEV	October 2017
Scenario-ontwikkeling energievoorziening 2030	SOE	June 2014
Energy [r]evolution	ER	May 2013
Nederland 100% Duurzame energie in 2030	NDE	March 2014
Verkenning energievoorziening 2035	VE	July 2017
Calculations of Klimaatakkoord	KA	2019

Agent-based modelling approach

After the scenarios were dissected, the NEV was chosen for the ABM analysis. The NEV was analysed because this scenario contains the most technological detail, has the longest history of all scenarios, and is the most prominent.

The scenarios were analysed using the Energy Modelling Laboratory (EMLab), which is an open-source Java model. The agents in EMLab can invest in additional power plants or decommission existing ones. They base their investment decisions on the expected future fossil fuel, CO2 and electricity prices. Additionally, investments by other agents are also considered. Predictions are based on historical data, but these predictions are unable to precisely predict the future. Predictions by the energy companies are therefore sub-optimal. In EMLab, fossil fuel and CO_2 prices, electricity demand, existing power plants, and investment and maintenance costs can be adjusted. For some parameters, such as the price of constructing natural gas power plants, numbers are not provided in scenarios. When these numbers were not provided, the values as used in Richstein et al. (2014) were taken. The analysis of these scenarios was conducted by ensuring that the input parameters for the scenarios are used as input parameters for EMLab. Each analysis was ran ten times in EMLab. In the displayed figures and tables, the aggregate of all these runs was displayed.

Once the initial conditions for EMLab were calibrated to the starting conditions used by the scenarios, the outcomes were compared in R studio. This comparison was made on the installed capacity, electricity produced, and electricity prices in 2030 between EMLab and the scenario in question. When EMLab did not reach similar values as the scenario, parameters were changed. Parameters that could be changed were the price of constructing new power plants, fossil fuel prices, and other policy options such as a ban on constructing additional fossil fuel technology.

Results

Firstly, table 1 is filled in based on the contents of the scenarios. Secondly, the NEV estimates and the EMLab results are displayed. Finally, the relation between the price of solar and the final installed capacity in 2030 is shown.

The research required for constructing table 3 showed that the NEV, SOE, NDE, VE, and KA all contained no agent-based models (Schoots, Hekkenberg & Hammingh, 2017; Rooijres, Schepers, Van Gerwen & Van der Veen, 2014; Urgenda, 2017; Weeda & Smekens, 2017; Van Hout et al., 2019).

Table 3. Scenario classification.

Characteristic	NEV	SOE	ER	NDE	VE	KA
General type	Predictive	Explorative	Normative	Normative	Explorative	Explorative
Method	Forecasting	Backcasting	Forecasting	Backcasting	Forecasting	Forecasting
Subject	Area-based	Area-based	Area-based	Area-based	Area-based	Area-based
Timescale	2016-2030	2012-2030	2010-2050	2015-2030	2013-2035	2015-2030
Spacial	Energy sector	Energy sector	Energy sector	Energy sector	Energy sector	Energy sector
Data	Quantitative & Qualitative	Quantitative & Qualitative	Quantitative & Qualitative	Quantitative & Qualitative	Quantitative & Qualitative	Quantitative & Qualitative
Level of deviation	BAU	BAU and unconventional disruptions	BAU and unconventional disruptions	BAU and unconventional disruptions	BAU and unconventional disruptions	Unconventional disruptions
Level of integration	High	High	High	High	High	High
Method	Fully probabilistic approach	Alternative scenario approach	Alternative scenario approach	Alternative scenario approach	Both approaches	Both approaches
Fossil fuel prices	IEA New Policies and WLO	Not defined	IEA Current Policies and own predictions	IEA New Policies	IEA and own predictions	IEA and own predictions
CO2 prices	Taken from WLO	Not defined	Own predictions	Own predictions	Own predictions	Taken from WLO and own predictions
Electricity demand	Constant demand	17.6% increase in demand	Not defined	25% increase in demand	Constant demand and own predictions	5% increase in demand
Innovation	Literature on learning curves for renewables	Expert opinions	Assumptions not clear	Assumes current state-of-the-art technologies	Literature on learning curves for renewables	Literature on learning curves for renewables
Policies	Current policies and planned policies	Current policies	International policies but not specific Dutch policies	Current policies	Different policy pathways	Planned policies

Figure 1 displays the NEV estimates for installed capacity. The NEV estimates natural gas to decrease by roughly 50% between 2015 and 2030. Solar capacity increases from 1.5GW in 2015 to 14 GW in 2030. Wind increases from 3.3 GW to 19 GW in 2030. In figure 2 the EMLab results can be seen. For figure 2a the demand as estimated by the NEV was used. For figure 2b, a demand increases of 15% between 2015 and 2030 was used. In order to reach figure 2 with EMLab, firstly the capital costs of solar energy had to be reduced to 0.35 €/W for figure 2a and to 0.325 €/W for figure 2b. Figure 2 shows that in the ABM analysis more natural gas is commissioned compared to the NEV estimates. Especially when demand is increased, almost 10 GW of OCGT capacity is installed between 2015 and 2030. The only way the NEV estimates could be obtained in EMLab was by prohibiting natural gas investments. In figure 3 the EMLab results are displayed for when natural gas investments are prohibited. Compared to figure 2, the solar prices for figure 3 could be higher. For figure 3a the capital costs were 0.39 €/W and for figure 3b 0.36 €/W

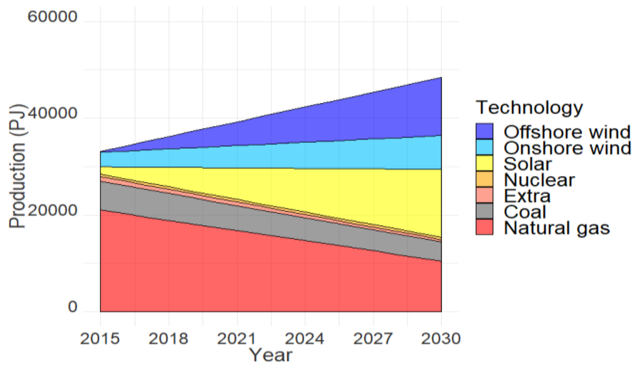

Figure 1. NEV estimate for the installed capacity.

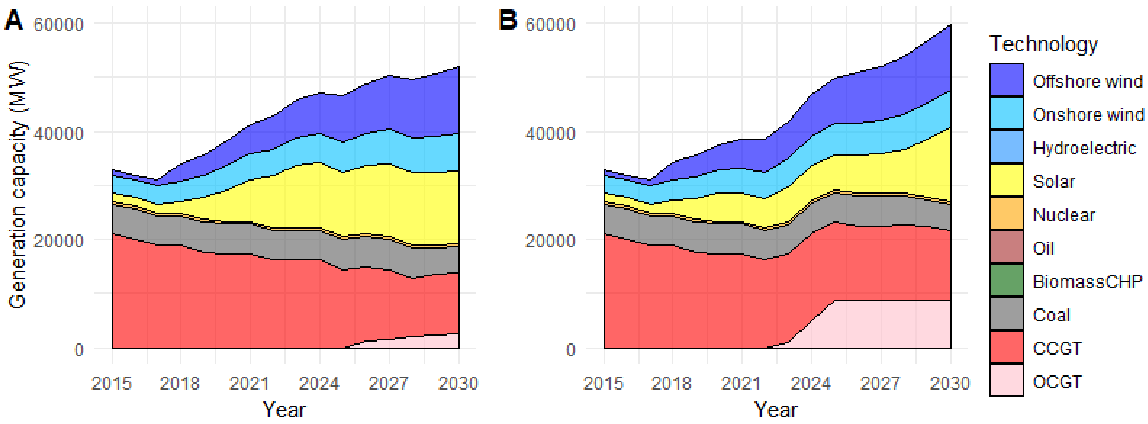

Figure 2. EMLab analysis of the NEV for similar solar capacity

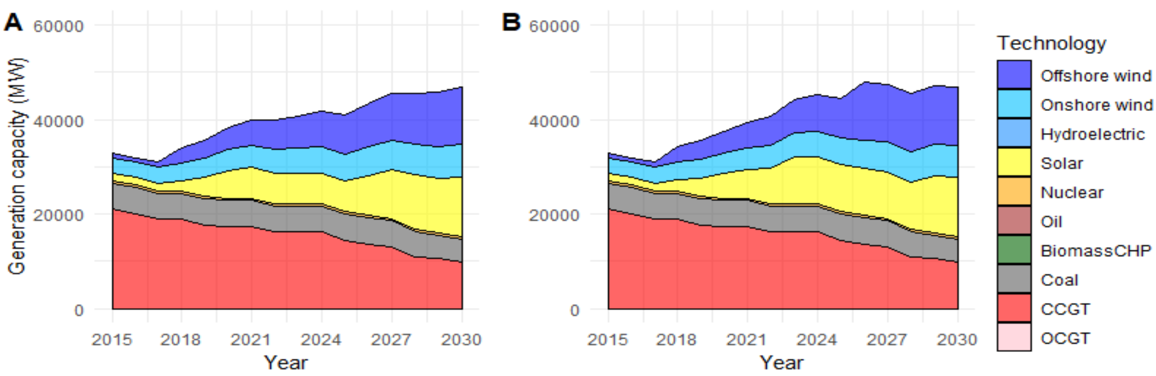

Figure 3. EMLab analysis of the NEV conform the NEV estimates

In figure 4 the relation between the capital costs of solar in 2015 and the energy mix in 2030 can be seen for the constant demand. For prices between 0.33 €/W and 0.45 €/W, the amount of installed solar capacity in 2030 changes is greatly depending on the price. Furthermore, it seems that for higher amounts of solar installed solar capacity in 2030, more OCGT is installed and less CCGT.

In figure 5 the NEV estimates for the electricity price can be seen. In figure 6a the electricity prices for the constant demand can be seen. In figure 6b, the prices for the increase in demand are displayed. The average price in the constant demand analysis falls in the bandwidth of the NEV. Furthermore, it is only 4 €/MWh lower in 2030 than the NEV estimate. For the increase in demand the average price is almost 200 €/MWh due to the many hours where the price is the Value of Lost Load (VOLL). In order to improve visibility, the VOLL was displayed as 200 €/MWh. However, for this analysis the actual VOLL was 2000 €/MWh. The blue horizontal line is the average price in 2030.

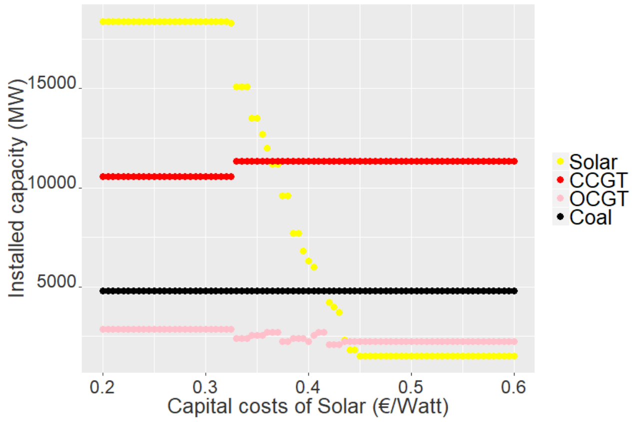

Figure 4. Relation between the price of solar and the energy mix in 2030 for a constant demand.

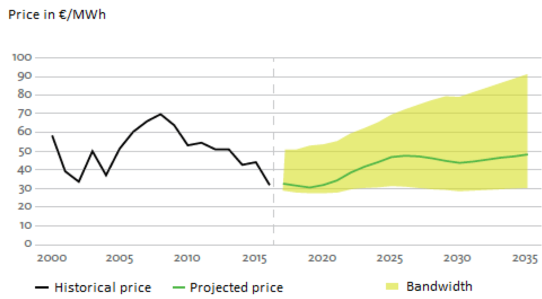

Figure 5. NEV electricity price estimates.

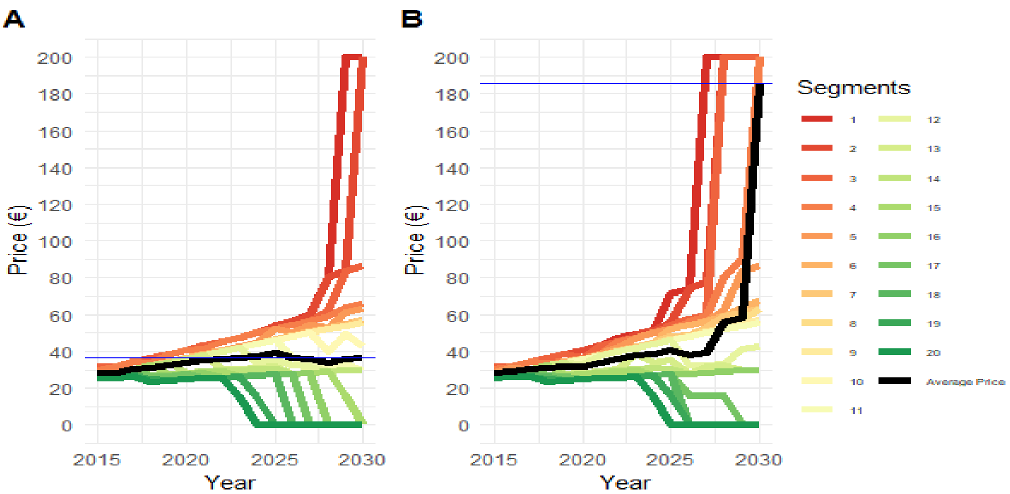

Figure 6. EMLab analysis of the NEV for electricity prices conform the NEV estimates for capacity.

Discussion

In table 4 the results of the ABM analysis have been combined into a comparison to the estimates of the NEV scenario. For each variable it has been indicated whether the ABM analysis outcome was similar (S), similar after policy intervention (SPI), similar after financial adjustment (SFA), or different (D). One column represents the comparison between the EMLab analysis for the constant demand, while the other column represents the comparison between the EMLab analysis for the increased demand.

Table 4. Results of ABM analysis compared to NEV estimates

NEV estimates	Constant demand	Increased demand
Installed solar capacity in 2030	S	S
Installed wind capacity in 2030	S	S
Installed coal capacity in 2030	S	S
Installed natural gas capacity in 2030	SPI	SPI
Average electricity price in 2030	S	D
Maximum electricity price in 2030	D	D
Minimum electricity price in 2030	D	D

The constant demand analysis shows that with additional solar SDE+ subsidies, the outcome of the EMLab analysis for solar installed capacity is similar to the NEV estimates for 2030. For the wind power capacity in 2030, the results are also similar. This is because wind power projects until 2030 are already planned by the Dutch government and the energy companies in the EMLab analysis do not invest into additional wind power on top of these planned investments. For coal both the NEV estimates and the EMLab analysis reach the same value in 2030.

In the EMLab analysis, more gas is commissioned than is estimated by the NEV. This is because current Dutch CCGT plants are decommissioned after reaching the age of 40, which is their expected lifetime. In order to compensate for this decommissioning, the energy producers in the EMLab analysis invest in additional fossil fuel capacity. Thereby, it seems that the additional renewable capacity is unable to prevent these investments into natural gas. Even when the price of natural gas is doubled compared to WEO estimates, the total natural gas capacity in 2030 is still higher than the NEV estimates. This means that the energy companies in EMLab expect investments in natural gas to be more profitable than the NEV expects. Only when natural gas investments are prohibited, are the NEV estimates reached in EMLab (Figure 3a).

Figure 6a shows that a ban on natural gas investments still leads to the same electricity price estimates of the NEV (Figure 5). The NEV estimates are slightly higher, but since the NEV contains interconnectivity while EMLab does not, combined with the estimate of the NEV that the Netherlands will be a electricity exporting country in 2030, average prices are expected to be higher (Di Cosmo, Bertsch, & Deane, 2016).

Figure 6b shows that the previously advocated policy intervention of prohibiting natural gas investments can have great consequences once other parameters such as demand change. Therefore, even though certain measures could limit the negative consequences of imperfect information, these measures have to be carefully explored, as they could counter-productive once the situation changes.

Conclusion

The classification and dissection of the scenarios showed that agent-based models are not used yet to develop energy scenarios for the Netherlands. The ability of the ABM approach to reach similar results to the scenario estimates, while also providing additional insights regarding the impacts of uncertain behaviour, shows the added value of incorporating ABM in scenario developing. For the development of future scenarios, the inclusion of ABM would improve the insights on possible occurrences of overcapacity and highlight how behaviour might influence the sector.

Bibliography

Beckman, J., Hertel, T., & Tyner, W. (2011). Validating energy-oriented CGE models. Energy Economics, 33(5), 799–806.

Bezdek, R. H., & Wendling, R. M. (2002). A Half Century of Long-Range Energy Forecasts: Errors Made, Lessons Learned, and Implications for Forecasting. 18.

Böhringer, C. (1998). The synthesis of bottom-up and top-down in energy policy modeling. Energy Economics, 20(3), 233–248.

Börjeson, L., Höjer, M., Dreborg, K.-H., Ekvall, T., & Finnveden, G. (2006). Scenario types and techniques: Towards a user's guide. Futures, 38(7), 723–739.

Bradfield, R., Wright, G., Burt, G., Cairns, G., & Van Der Heijden, K. (2005). The origins and evolution of scenario techniques in long range business planning. Futures, 37(8), 795–812.

Chappin, É. J. L. (2011). Simulating energy transitions. Next Generation Infrastructures Foundation.

Dam, K. H. van, Nikolic, I., & Lukszo, Z. (Eds.). (2013). Agent-based modelling of socio technical systems. Dordrecht ; New York: Springer.

Den Ouden, B., Lintmeijer, N., Bianchi, R., & Warnaars, J. (2018). Eindrapportage_systeemvraagstukken_en_afhankelijkheden_in_de_energietransitie_28052018_final.pdf.

Di Cosmo, V., Bertsch, V., & Deane, P. (2016). Impact of new interconnection lines on the EU electricity market. 2016 13th International Conference on the European Energy Market (EEM), 1–5.

Edmonds, B. (2017). Different Modelling Purposes. In B. Edmonds & R. Meyer (Eds.), Simulating Social Complexity (pp. 39–58).

Farmer, J. D., & Foley, D. (2009). The economy needs agent-based modelling. Nature, 460(7256), 685–686. https://doi.org/10.1038/460685a

Gowrisankaran, G., Reynolds, S. S., & Samano, M. (2011). Intermittency and the Value of Renewable Energy. 58.

Hansen, P., Liu, X., & Morrison, G. M. (2019). Agent-based modelling and socio technical energy transitions: A systematic literature review. Energy Research & Social Science, 49, 41–52. https://doi.org/10.1016/j.erss.2018.10.021

Jefferson, M., & Voudouris, V. (2011). Oil scenarios for long-term business planning: Royal Dutch Shell and generative explanation, 1960-2010. 41.

Keles, D. (2013). Uncertainties in energy markets and their consideration in energy storage evaluation. 260.

Lijesen, M. G. (2007). The real-time price elasticity of electricity. Energy Economics, 29(2), 249–258.

Lund, H., Arler, F., Østergaard, P., Hvelplund, F., Connolly, D., Mathiesen, B., & Karnøe, P. (2017). Simulation versus Optimisation: Theoretical Positions in Energy System Modelling. Energies, 10(7), 840. https://doi.org/10.3390/en10070840

Ma, T., & Nakamori, Y. (2009). Modeling technological change in energy systems From optimization to agent-based modeling. Energy, 34(7), 873–879.

Macal, C. M., & North, M. J. (2010). Tutorial on agent-based modelling and simulation. Journal of Simulation, 4(3), 151 -162. https://doi.org/10.1057/jos.2010.3

McFarland, J., Reilly, J., & Herzog, H. (2002). Representing Energy Technologies in Top-down Economic Models Using Bottom-up Information. 26.

Peterson, G. D., Cumming, G. S., & Carpenter, S. R. (2003). Scenario Planning: A Tool for Conservation in an Uncertain World. Conservation Biology, 17(2), 358–366.

Pfenninger, S., Hawkes, A., & Keirstead, J. (2014). Energy systems modeling for twenty-first century energy challenges. Renewable and Sustainable Energy Reviews, 33, 74 -86.

Rooijers, F., Schepers, B., van Gerwen, R., & Van der Veen, W. (2014). Scenario ontwikkeling energievoorziening 2030.CE Delft and DNV GL, 14, C93.

Rutte III, K. (2017). Regeerakkoord: Vertrouwen in de toekomst.

Schoots, K., Hekkenberg, M., & Hammingh, P. (2017), Nationale Energieverkenning 2017. ECN-O--17-018. Petten: Energieonderzoek Centrum Nederland

Urgenda. (2017). Nederland 100% Duurzame Energie in 2030. Retrieved from https://www.urgenda.nl/wp-content/uploads/Urgenda-Rapport-DuurzameEnergie-in -2030-v2 -2017.pdf

Van Beeck, N. M. J. P. (1999). Classification of energy models. FEW Research Memorandum. Operations research, Tilburg.

Van Hout, M., Koutstaal, P., & Özdemir, Ö. (2019). Achtergrondrapport effecten ontwerp klimaatakkoord: Elektriciteit. 28.

Van Notten, P. W. F., Rotmans, J., van Asselt, M. B. A., & Rothman, D. S. (2003). An updated scenario typology. Futures, 35(5), 423–443. https://doi.org/10.1016/S0016 -3287(02)00090-3

Van Vuuren, D. P. (2001). Mitigation scenarios in a world oriented at sustainable development: The role of technology, efficiency and timing. Climate Policy, 22.

Weeda, M., & Smekens, K. E. L. (2017).

Weijermars, R., Taylor, P., Bahn, O., Das, S. R., & Wei, Y.-M. (2012). Review of models and actors in energy mix optimization – can leader visions and decisions align with optimum model strategies for our future energy systems? Energy Strategy Reviews, 1(1), 5–18. https://doi.org/10.1016/j.esr.2011.10.001

Zeng, Y., Cai, Y., Huang, G., & Dai, J. (2011). A Review on Optimization Modeling of Energy Systems Planning and GHG Emission Mitigation under Uncertainty. Energies, 4(10), 1624 1656. https://doi.org/10.3390/en4101624