The Impact of Extreme Weather Conditions on a Renewable Dominated Power System in Germany and Measures to Maintain Security of Supply

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Executive Summary

With an increasing share of photovoltaic and wind in the German generation mix, the power supply reduces its CO_2 emission and becomes more weather dependent. In order to guarantee the security of supply, the volatile power output by the renewables asks for compensation by other sources. These backup technologies have to cope with a variety of scarcity cases, ranging from single peaks of uncovered load to longer scarcity periods. During winter times, these scarcity incidents show their most extreme form and overlap in some weeks. The German news calls this phenomenon “kalte Dunkelflaute” or only “Dunkelflaute” (analogously translated “energy drought during darkness and cold”).

The need for backup technologies goes not along with a certain cost recovery. As the last dispatched entity in the market, they need to cover their fixed costs by scarcity prices. Depending on various factors, such as the weather conditions and the availability of short-term flexibility, it is difficult to predict the level of scarcity prices. Uncertain investment conditions lead to investment restraints and harm the security of supply. At the same time, frequent scarcity prices would contradict the principle of a secure energy supply with a limited financial burden for the consumers. The regulator is in a dilemma.

Rewarding the contribution to the security of supply is an option to stimulate investments in backup technologies. The so-called capacity mechanisms are an intervention into the energy-only-market (EoM) which is known to organize the energy supply in the most efficient way. The principle decision of an intervention and its design requires a sounds judgment and the consideration of many factors. By presenting the challenges of future scarcity moments, the cost recovery conditions for backup technologies and examples for cost recovery measures, the thesis aims to contribute to the on-going discussion by answering the research question “How to maintain the security of supply under extreme weather conditions in a renewable dominated electricity system in the most cost-efficient way?”.

It is addressed by a simulation with the agent-based model AMIRIS and accompanying analyses based on literature reviews and calculations. In the beginning, a cost comparison of backup technologies (chapter 3) and a multi-criteria decision analysis for capacity mechanisms (chapter 4) are examined. The most cost-efficient forms of each analysis are processed subsequently.

After an introduction into the model (chapter 5) and the simulation process (chapter 6), the variations of scarcity (chapter 7) and cost recovery (chapter 8) according to two contrary weather years and the availability of battery storages are presented. Three scarcity indicators help to characterize the scarcity in the first step and indicate the dimensions of the backup capacity in the second step. A sensitivity analysis to test the robustness of the simulation results is examined in chapter 9. Lastly, two measures to bridge the lacking cost recovery for the backup technologies are presented. The resulting costs of the energy supply for the consumers are compared for the two measures and the system with scarcity prices without any intervention (chapter 10).

The thesis describes the challenge of increasingly volatile market conditions and recommends measures to mitigate their risks. The main findings are presented by the four guiding hypotheses in the following.

1. ***The level of scarcity varies substantially with the weather conditions***

For every weather condition, single moments occur in which a high residual load and limited flexibility lead to an extreme peak of the uncovered load. The simulation shows the same level for the maximum hourly peak for every scenario. In contrast to that, the aggregated uncovered load per year varies significantly for the extreme weather year 2010 with a low renewables output and the mild weather year 2007 with a high renewable output. The scenario with the weather year 2010 asks for 25 percent more additional energy to cover the demand than the one with the mild weather year 2007.

The severity of scarcity becomes explicit when one considers the uncovered load of the longest scarcity period of each simulated year. In the scenarios with the weather year 2010 and 15 GW installed battery storage, it lasts for almost three days and contains 0.25 percent of the yearly uncovered load. This period by mid-February includes the maximum peak of uncovered load and is surrounded by other long scarcity periods. In this sense, it is a stress test for the electricity system.

The situation changes for the mild weather year 2007. The longest duration of scarcity asks for less than a half of the energy of 2010. The difference of additionally requested energy and capacity makes it explicit how difficult it is to design a well-tailored backup mix for these scarcity moments.

2. ***The short-term flexibility providers lower the need for backup capacity but cannot substitute it***

The emergence of short-term flexibilities, such as battery storage, is a mixed blessing for the security of supply. On the one hand, it balances the energy supply in moments with high and low prices and closes gaps between demand and supply. Looking at the scenario with the extreme weather year, the implementation of 15 GW battery storage divides the uncovered load per year in a half. On the other hand, it reduces the income basis for the backup technologies and is, therefore, a further factor of uncertainty for investments.

At the same time, battery storage can hardly address situations of extreme scarcity alone. Only 10 percent of the missing energy can be covered by the battery storage during the longest scarcity period. The maximum uncovered load cannot be reduced at all by the battery storage.

The correlation of extreme scarcity peaks and long scarcity periods gives the battery storage hardly any opportunity to charge during the extreme scarcity periods. For instance, more than one-third of the extreme peaks (in this case defined as 20 GW and more) is surrounded by a period of scarcity of 5 hours and longer.

The knowledge about future prices impacts the ability of the battery storage to address scarcity hours. If the so-called foresight is extended from one day to one week, the uncovered load per year can be reduced by 20 percent. However, the positive effect of the longer foresight is bounded by the technical limitations of the battery storage. In the presented scenarios, no additional mitigation of the scarcity can be achieved in times of the Dunkelflaute by a foresight of one week. Also, a longer foresight than one week cannot reduce the uncovered load per year any further.

Conclusions can be drawn about the suitability of the price sequences to support the bidding of the battery storage. It is noticeable that the longer foresight increases the number of used high prices but does not have the same effect on the low prices. Upcoming high prices seem to be missing to create an additional value by charging more energy during the low prices. This indicates a limited fit of the prices sequences for charging and discharging of the battery storage.

All in all, the battery storages are restricted by their technical limitations and the sequence of market prices. Despite their positive effect on scarcity, they cannot substitute long-term backup technologies.

3. ***The level of cost recovery for backup technologies on the EoM is not sufficient and depends strongly on the weather conditions and the availability of battery storage***

Due to its ability to react fast to scarcity signals and its relatively low fixed costs, gas turbines supplied with fossil gas are selected as backup technology. The constant level of the scarcity peak for all scenarios gives a clear indication for the required backup capacity. At the same time, the changing request of the backup energy for the different weather conditions and availability of short-term flexibility impacts their cost recovery.

In the simulated case, the backup technologies do not leverage their dominant market position in times of scarcity and only bid their marginal cost. This leads to a negative profit margin for every scenario negative. With the implementation of 15 GW battery storage, it becomes four times lower. The optimized bidding with the longer foresight decreases the margin additionally by 25 percent. The lower request of the mild weather year leads to a decrease of 83.5 percent.

Assuming that a further expansion of renewables would lead to a larger price spread and a more constant level of scarcity, the implementation of a power-to-methane to create synthetic gas from excess energy is an interesting option. Due to limitations of the model, power-to-methane was not simulated as backup technology, but the insights from the simulation with the gas turbine are transferred in a simplified calculation. It results in a higher (but still negative) profit margin for power-to-methane. At the same time, it needs to be considered that the smaller fixed costs base of the fossil gas application can adapt better to changing requests of backup energy. An implantation of a gas turbine supplied with fossil gas and later with syntactic methane would address both incidents.

Solely the availability of suitable backup technologies will not lead to investments without a positive business case. Therefore, some measures to handle the lacking cost recovery are presented in the next paragraph.

4. ***A well-designed regulatory intervention which rewards the contribution to the security of supply can reduce the costs for the consumer and improves the supply ratio***

The skepticism about the ability of the EoM to recover the costs of capital intense backup technologies is reinforced by the analysis. At the same time, no final assessment to which extent the invisible hand of the market can trigger investments in backup capacity and at which point a regulatory intervention is needed can be given in the course of the thesis. It only aims to pinpoint measures to improve the cost recovery and indicate their financial burden on the consumer.

If a capacity mechanism does not only trigger investments in backup capacity but incites a system friendly behavior by all market participants, the security of supply can be maintained in the most cost-efficient way. In this sense, the MCDA highlights the concept of capacity subscriptions. By its self-rationing approach, it gives the consumers the option to decide whether they prefer to invest into backup capacity or contribute to the security of supply by reducing their consumption at peak times. The simplified calculation for the industrial consumers demonstrated its efficiency enhancement.

As an alternative for improving the cost recovery, backup technologies can exhaust their dominant market position in scarcity times by including markups in their bids. As other market participants benefit from the increased prices as well, the measure with markups leads to higher costs of the energy supply for the consumers than the one with capacity subscriptions.

Comparing the costs of energy supply in case of the EoM with and without a capacity subscription, the acceptance of scarcity prices leads to significantly higher costs for the consumer every year. Assuming that the scarcity prices would trigger investments in backup capacity, this would be at least the case during the lead time between the investment decision and commissioning of the backup technology. For the simplified calculation, the costs of energy supply are 12.9 times higher in the extreme case of scarcity and 5.2 times higher for a sensitivity of only 50 percent of the missing secured capacity.

Overall, the calculations show the increases in efficiency resulting from capacity subscriptions and the reduction of the financial burden for the consumers. The design of a well-tailored regulatory intervention is a complex matter that carries the risk of maladjustments and false incentives. The design of capacity subscriptions, the extent of market power during scarcity time and the composition of a well-balanced flexibility mix which considers short-term flexibility potentials and long-term backup technologies is subject for further research.

In conclusion, the thesis shows that suitable backup technologies are available and needed in an electricity system with a high share of renewables. At the same time, their cost recovery by the EoM is insufficient and is deteriorated in case of a mild weather year, a high level of battery storage and their qualification of forecasting the future dispatch accurately. The concept of capacity subscriptions is recommended as a measure to improve the cost recovery, decrease the risk and enhance efficiency.

Acknowledgment

Nothing worth having comes easy. This widespread wisdom counts for this master thesis as well. There was sometimes a thin line between growing by facing challenges and ending in chaos. I am extremely grateful to have a graduation committee which always supported me to stay on the right side of that line. In this sense, I would like to thank my supervisors Dr. Laurens de Vries, Dr. Martijn Warnier, Dr. Marc Deissenroth and Dipl. Kristina Nienhaus.

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I consider myself lucky to be supervised by people who do not only possess extensive knowledge but are also willing to share it in a kind and patient way. This is expressed, for instance, by the fact that Kristina and Marc took the time to discuss the progress of my thesis every week. Each time when we stood next to the blackboard and discussed some challenging content, I felt the magic of spreading knowledge and continuous enhancement. This kept me motivated through the entire course of the thesis.

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Sabine Pelka
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List of Abbreviations

BMWi	Bundesministerium für Wirtschaft und Energie
CCGT	Combined Cycle Gas Turbine
DLR	Deutsches Zentrum für Luft- und Raumfahrt e.V.
ENTSO-E	European Network of Transmission System Operators for Electricity
EoM	Energy-only-market
Etc.	Et cetera
ETS	Emission Trading Scheme
EUR	Euro
EUR/kW	Euro per kilowatt
EUR/t	Euro per tone
GW	Gigawatt
GWh	Gigawatt hour
h	hour
IEE	Fraunhofer-Institut für Energiewirtschaft und Energiesystemtechnik
kWh	Kilowatt hour
MCDA	Multi-criteria decision analysis
Mio.	Million
MWh	Megawatt hour
O&M	Operation and Maintenance
PV	Photovoltaic
TWh	Terawatt hour

List of Symbols

Symbol	**Description**	**Unit**
C_{cs}	Specific Costs of Capacity Subscriptions	EUR/GW
u_{cs}	Requested Amount of Capacity Subscriptions	GW
C_{DS_i}	Specific Costs of Demand Shedding per Industry i	EUR/GWh
l_0	Uncovered Load without Demand Shedding (u_{cs} deducted)	GWh
l_i	Remaining Load after the Use of Demand Shedding by Industry i	GWh

1 Research Definition

1.1 Introduction

With a share of at least 80 percent of renewable energy sources on the electricity consumption in 2050 (BMWi, 2016), the German electricity production reduces its CO_2 emissions and becomes more sustainable. However, at the same time, the dependency of the generation mix of the weather situation increases and the guarantee of a secure energy supply for Germany becomes a challenge.

Especially winter days with fog, still air and a high energy demand (the so-called Dunkelflaute) are a stress test for the new energy system. For instance, on the 24. January 2017 the overall electricity demand of 83 gigawatts (GW) could only be covered by max. 3 GW renewables (Agora, 2018). Currently, these shortcomings are bridged by conventional power plants and cross-border imports. With the increasing share of photovoltaic and wind energy in the generation mix, conventional power plants will be replaced. Therefore, special technologies for moments with a shortage of power supply (the so-called backup technologies) are required to maintain the security of supply.

Whereas the bids on the wholesale market reflect the marginal costs of the participants, their fixed costs need to be covered by the difference of the market clearing price and their marginal costs. In the microeconomic theory, the full costs of the price setting entities need to be covered by scarcity prices, which are significantly higher than the marginal costs of the last dispatched entity. While the technical price cap for the day-ahead market is defined at 3 000 EUR/MWh, the highest price for the Phelix Day Peak 2015 was 65 EUR/MWh (BNetzA, 2016). Even if the prices start to rise, the questions whether the number of scarcity prices is sufficient to cover the total costs and whether the investors are willing to invest under these conditions remains open. The uncertainty of cost recovery lead to investment restraints and impede the security of supply in a renewable dominated power system.

1.2 Problem Definition

The problem of a lack of investments in backup capacity becomes especially explicit for the rare case of the Dunkelflaute in a by renewables dominated power system. For some weeks during the winter, high-pressure areas can lead to an absent production of wind and solar energy at the same time. Two side effects worsen the situation additionally. First, not only the electricity supply is scarce, but also the demand tends to be high during these winter weeks. This results in an overall high load which still need to be covered by other sources than renewables (the so-called residual load). Second, occasionally the Dunkelflaute is not only a regional effect but an issue for entire Central-Western Europe due to large-scale weather patterns. In this case, the mitigating effect of imports from neighboring countries is limited (Becker, 2018; Grams, Beerli, Pfenninger, Staffell, & Wernli, 2017). Consequently, units which are tailored to bridge these scarcity moments are needed.

The wholesale market sends investment signals in form of price peaks. The signals for the investment in backup capacity are highly dependent on the weather conditions. The uncertain frequency and intensity of scarcity moments give investors no solid indication for the level of needed backup capacity and the conditions of the cost recovery. The lacking perspective on the long-term weather development is not compatible with the security needs of the investors and payback periods of up to 30 years for backup technologies (Tomschi, 2013).

Besides the weather conditions, other uncertain parameters deteriorate their business case. For instance, short-term flexibility providers cannot bridge long scarcity periods with high peaks of uncovered load, but they can reduce single scarcity peaks and lower the extreme prices (Landinger, Bünger, Raksha, Weindorf, Simón, et al., 2014). On the one hand, this has a positive effect on the security of supply from the system perspective, on the other hand, a negative effect on the cost recovery for the backup technologies.

The risk of the uncertain cost recovery can be limited by additional payments for their service of maintaining the security of supply. Such interventions in the market design are called capacity mechanisms. Different forms of such mechanisms are currently discussed by market experts, regulators, and politicians. Such interventions require a solid judgment to ensure that they fulfill their purpose without disrupting the market and creating inefficiencies.

These issues are underpinned by a literature review and translated into four hypotheses which shape the following research.

1.2.1 The Impact of the Weather on the Security of Supply

Seasonal differences in the demand are a well-known uncertainty factor for the historic generation portfolio which was dominated by conventional power sources. With the increasing share of weather depended on renewables, also the supply side differs from season to season. For instance, the evaluation about the yearly distribution of production surpluses by renewables by Schill, 2013 shows that up to 36 percent of the yearly surplus in 2022 is concentrated in the month of May (Schill, 2013).

The weather does not only differ from month to month but from year to year. The need for long-term planning by conventional power plants and the system operator is stressed. Their role in the market and business case changes fundamentally. The impact of the weather on the security of supply is demonstrated by several publications (Becker, 2018; Fraunhofer IEE, 2018; Huneke, Perez Linkenheil, & Niggemeier, 2017; Pfluger et al., 2017).

In 2017, the German energy consultancy Energy Brainpool published on behalf of Greenpeace Energy e.V. a report about the security of supply in extreme weather situations (Huneke et al., 2017)[1]. In 2018, the German research institute Fraunhofer Institute for Energy Economics and Energy System Technology (IEE) published their scenarios for different weather years with regard to the mitigation of climate change (Fraunhofer IEE, 2018). A working package of the project about long-term forecasts for the power sector by the Federal Ministry of Economics, Technology, and Energy (BMWi) deals with the impact of extreme weather conditions on the security of supply. The report of the working package cannot be considered in the thesis, as it is not published by now, but it highlights the importance of the topic (BMWi, 2018).

The German Meteorological Service (DWD) analyzes the coincidence of absent power production by the different renewable technologies. For the years 1995 to 2015, onshore wind energy did not produce power for a period of two days 23 times per year on average. The lacking power production can be compensated by a mix with other renewables. If the aggregated production by wind onshore, offshore

[1] A limited neutrality needs to be taken into account, as the report was commissioned by the environmental NGO.

and photovoltaic is evaluated, only two times a two days period of non-production per year occurred (Becker, 2018). These numbers give an interesting insight into the distribution of renewable production. At the same time, information about the level of production during these times, the coincidence with the hourly demand and the absent production during shorter periods than two days would be needed to give a comprehensive picture about the security of supply. This is done by the other two publications about the Dunkelflaute.

Huneke et al., 2017 uses weather years from 2006 to 2016 and merges them with the generation mix of 2016 and 2040 (Huneke et al., 2017). For the latter one, they assumed that 69 percent of the gross electricity consumption is covered by renewables. Fraunhofer IEE, 2018 uses the weather years from 2006 to 2012 and assumes a 95 percent renewable scenario with a significant degree of sectoral coupling for 2050 (Fraunhofer IEE, 2018).

The extreme situation with the highest level of uncovered residual load is highlighted. Fraunhofer IEE, 2018 presents the month January 2010 (excluding the first week) as the period for Dunkelflaute. Huneke et al., 2017 selects two weeks at the end of January 2006.

The different input parameters and indicators for the output impede a comparison of the results. For Fraunhofer IEE, 2018, the high degree of sectoral coupling and imports result in a maximum gap between demand and supply of 30 GW for the weather year 2010. The uncovered load ranges from 1 terawatt hour (TWh) for 2007 to 3.9 TWh for 2010. Huneke et al., 2017 indicates the average residual load during the two weeks of Dunkelflaute as an indicator of scarcity. For 2006, the average is 72.8 GW (Huneke et al., 2017). In contrast to that, Fraunhofer IEE, 2018 shows a lower maximum peak of 50 GW, which is partly covered by industrial coproduction and storage. The uncovered load of the two weeks by Huneke et al., 2017 ranges from 4.47 TWh for 2016 to 22.88 TWh for 2006.

All in all, the reports underline that even under favorable conditions for the power system (e.g. high sectoral coupling and import) backup capacity is needed. According to Huneke et al., 2017, the backup technologies only account for 0.1 to 3 percent of the traded energy per year (Huneke et al., 2017).

The low level of requested backup energy, its yearly differences and the unpredictable pattern of the weather years impede their cost recovery (Marković & Koch, 2005; Suri et al., 2007; Wachsmuth et al., 2013).

Hypothesis 1: Apart from fluctuating, weather dependet renewables, other energy sources are needed as a backup to maintain the security of supply. The requested backup energy varies substantially with the weather conditions.

1.2.2 The Impact of Battery Storage on the Security of Supply

Battery storages are about to emerge in Germany. More than 80 000 battery systems for photovoltaic systems are installed right now (BSW Solar, 2018). Even though the German target of 1 Mio. electronic vehicles by 2020 is unlikely to be met considering the current number of 53 861 vehicles, the German government underlines their intention by announcing funding programs for the charging infrastructure in their coalition agreement (CDU, CSC, & SPD, 2018; Statista, 2018).

Products involving a battery can be utilized for their specific purpose of acquisition (e.g. driving the electric vehicle or storing the energy by the rooftop photovoltaic systems) or for trading the flexible energy. Due to the scope of the thesis, only the interaction on the wholesale market is considered. The limitations due to other use cases than the optimization on the wholesale market could limit the availability of their flexibility.

The storage generates a margin by charging during low prices and discharging during high prices on the wholesale market. The bidding strategy built on the price spread is called arbitrage. Thereby, the storages lower positive and negative extreme prices and reduce imbalances between demand and supply. Battery storage are characterized by a limited energy-to-power ratio. This implies that they can discharge only for a limited time ranging from one hour to one day (Sterner & Stadler, 2014)

The literature discusses two main use cases of battery storage. They can be either used in a system friendly way to stabilize it and lower the system costs (Sioshansi, Denholm, Jenkin, & Weiss, 2009; Zapf, 2017) or to maximize the profit of its owner (Conejero, Díaz, & Gomez, 2018; He et al., 2016; Majidi, Nojavan, & Zare, 2017; Simshauser, 2018). The tailored bidding for both objectives is only possible if the storage has sufficient information about the conditions of the dispatch in the following hours (Conejero et al., 2018).

In the case of profit maximization, the operator tries to avoid lowering the price if the lower price cannot be compensated by a higher sold quantity. This proceeding is only possible if one entity (or several well-coordinated entities) uses an arbitrary strategy. If more players with an arbitrary strategy compete against each other, they run the risk of lowering the prices and their income. Looking at the range of different owners of storage and trading aggregators in the market, a competitive environment is likely (Majidi et al., 2017).

The cannibalizing effect of storages in a competitive environment is also applicable to backup technologies. In this context, the effect of battery storage on the security of supply is ambivalent. The reduction of single scarcity peak has a positive impact on the system in the short-term but the reduced price signals for backup investment deteriorate the security of supply in the long run.

Hypothesis 2: Short-term flexibility providers, such as battery storage, lower the need for backup capacity but cannot substitute it.

1.2.3 Backup Technologies in the Energy-Only-Market

Two main decisions shaped the energy system as it is known today. Both intended to maximize the social welfare by enhancing efficiency. First, the dispatch between producers and consumers is organized on a competitive market which triggers actions of the participants via the price signal. As producers and consumers are the parties who strive for their own optimization and are aware of their options to choose, the transfer of the decision-making power from the regulator to them shall lead to the most efficient outcome (P. Joskow, 2006; Pérez-Arriaga, 2014).

Second, for the design of the market, short-term marginal pricing and energy as the main traded product are selected (Caramanis, Bohn, & Schweppe, 1987). Once a power plant is installed, the before made investment is seen as sunk costs and not reflected in the short-term bids of the wholesale market. By pricing the marginal costs, the sunk costs shall be recovered indirectly by the margin. In other words, the long-term investments are only covered by short-term pricing. This approach aims to create the most efficient generation mix and bidding patterns. It is disrupted by the increasing amount of non-dispatchable generators with low marginal costs. The challenge of cost recovery for the backup technologies is explained from the microeconomic perspective in the following.

The generation mix is designed for the different levels of load to cover. Broadly speaking, the base load is covered by generators with high fixed costs and low variable costs. As they run for the majority of hours over the year, the base load is covered in the most economically efficient way by these technologies. In contrast to that, the rare load peaks are covered by generators with low fixed costs and high variable costs. As they run only for few hours over the year, the peak load is covered in the most economically efficient way by the so-called peakers. Fluctuating renewables are excluded from the approach, as the coincidence of their output and hourly load cannot be scheduled. Therefore, they are deducted from the load. The so-called residual load is used for the analysis of the generation mix (Pérez-Arriaga, 2014; Schill, 2013).

For a better overview, the different residual load levels are ranked by their size in the load duration curve. As illustrated in figure 1, the load duration curve decreases with an increase of renewables (see graph below).

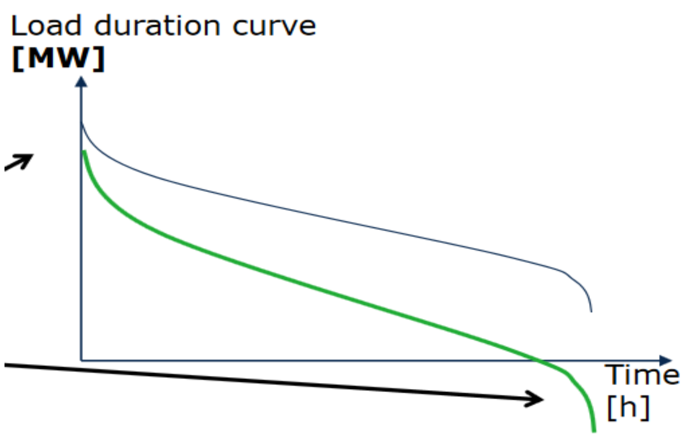

Figure 1: Change of load duration curve with the increase of renewables (green curve), Source: (Schill, 2013)

With the decrease of the residual load, the prices and full load hours of the conventional power plants decrease as well. Their cost recovery is impeded.

The situation is special for the peaker. Under the current market design, the fixed costs of the generation entities are covered by the margin between the market clearing price and their bid. If the peaker sets the market clearing price, it has no margin to recover its fixed costs. When a gap between requested demand and offered supply occurs, high scarcity prices based on the price of non-served energy can cover the fixed costs of the peaker. The problem of covering the fixed costs is also known as the missing money problem (Pérez-Arriaga, 2014).

In a renewable dominated power system, the baseload power plants are replaced by the renewables. The generation mix only consists of a high share of renewables and some peakers (in other words, backup technologies). Their cost recovery depends on the number of scarcity hours. It is neither ensured that the margin is sufficient to cover the fixed costs nor in which frequency the scarcity hours occur. For taking this uncertainty, the investors ask for an additional surcharge. The so-called risk premium increases the level of missing money for the backup technologies additionally (Cramton, 2017).

The risk assumption in return for a risk premium is a basic element of investment plans. Uncertainties connected to the procurements markets for fossil fuels and CO_2 certificates or price dynamics in the power market are translated into probabilities and its monetary impact in the worst case. Both aspects are multiplied for the risk premium (Groot, Richstein, & de Vries, 2013). Most of the uncertainties reoccur on a regular basis and level off within the investment period. In case of long-term investments for rare event of the Dunkelflaute, this approach runs the risk of being no applicable anymore. If the revenue differences are not likely to level off on a frequent basis within the investment time span, the risk level increases significantly and becomes hardly bearable for investors or for the consumers who need to pay the high risk premiums (Kovacevic & P, 2013).

Hypothesis 3: The backup technologies cannot recover their costs solely by the EoM. The level of cost recovery strongly depends on the weather and the availability of battery storage.

1.2.4 Pricing the Contribution on Security of Supply

The missing money problem is not only provoked by the short-term pricing but also by the determination of energy as the main traded product. Reliability is seen as a public good, which is not priced so far. Its value is only indirectly expressed by scarcity prices. The absent formation of a market is connected to the non-excludable character of reliability. The so-called freeriding reduces the willingness-to-pay of the consumers, as the consumers who do not want to pay for the security of supply profit from a secure energy supply nevertheless (Ostrom, 2010).

Regulatory interventions can organize the pricing of the service for providing security of supply. The so-called capacity mechanisms can stimulate investments in backup technologies. It is a fundamental decision whether investment incentives shall be given by the EoM and its scarcity prices or by capacity mechanisms. By accepting more frequent scarcity prices and the risk of lacking supply for some consumers, the potential of the EoM to incite new investments is exhausted. Even if the scarcity prices trigger new investments, the temporal offset between the investment decision and completed construction of a backup plant prolongs the period of lacking security of supply (Cramton, 2017).

It is doubtful that experiments which test the functionality of the EoM at the expense of the security of supply are socially acceptable. Frequent scarcity prices lead to high costs for the electricity supply for the consumers. (Bhagwat, Iychettira, Richstein, Chappin, & De Vries, 2017) compare the supply ratio and the overall costs for the consumers for the EoM and a market with a special kind of capacity mechanism, the capacity market. In case of a renewable dominated system, they demonstrate lower costs for the consumer and a higher supply ratio in case of the capacity mechanism.

Hypothesis 4: A well-designed regulatory intervention which rewards the contribution to the security of supply can reduce the costs for the consumer and improve the supply ratio.

1.3 Problem Statement and Research Question

The underlying knowledge gap between the changing scarcity condition depending on the weather conditions and the cost recovery for backup technologies is addressed by the following research question "How can the security of supply be maintained under extreme weather conditions in a renewable dominated system in an economically efficient way?". Thereby, the impact of the uncertain weather conditions and the available short-term flexibility on the cost recovery of backup technologies and measures to provide sufficient flexibility[2] for security of supply are presented.

2 Research Overview

The investigations are shaped by the hypotheses given in chapter 1. To define the possible future scarcity incidents and the cost recovery of backup technologies, an energy system with a high share of renewables is simulated by an energy dispatch model. In the first step, a certain level of investment restraints of secured capacity is assumed. In this constellation, the impact of the weather conditions and short-term flexibility on the security of supply is tested. Battery storage are selected as representative short-term flexibility provider. Thereby, the first and second hypotheses are investigated.

If the different scarcity incidents cannot solely be covered by the battery storage, a long-term backup technology is implemented in the second step. The cost recovery of the backup technology is evaluated for the different weather conditions and levels of installed battery storage. The backup technology is selected based on a technology pre-analysis which compares the costs of different backup technologies.

If the third hypothesis is confirmed and the total costs of the backup technology cannot be covered by its income from the EoM, measures to cover the costs deficit are analyzed. The costs deficit is transformed into additional revenue streams in simplified calculations. A market-based approach by which the backup technology exploits its dominant market position in scarcity times and a selected capacity mechanism are used as the basis for the additional revenue streams. The costs of the two measures for the consumers are compared to the current practice of accepting scarcity prices. The capacity mechanism is selected based on a multi-criteria decision analysis (MCDA). To limit the financial burden for the consumers, the selection of the capacity mechanism and the comparison of the market-based and regulatory measures for cost recovery focus on cost-efficiency.

The pre-analyses about backup technologies and capacity mechanisms are examined before the two-stage simulation by the energy dispatch model and the processing of the simulation results for an improved cost recovery are executed.

By highlighting the economic challenges of backup technologies under different market conditions and by presenting measures for cost recovery, the research question is addressed.

[2] Def. flexibility in this context: Ability to offer energy or postpone consumption when energy is scarce

3 The Cost Comparison of Backup Technologies

The future energy systems aim to be reliable, affordable and sustainable. These principles by the German government are the guiding theme for the evaluation of the backup technologies. Considering reliability and sustainability as benefits, the approach of a cost-benefit-analysis (CBA) could be used. ENTSO-E developed a comprehensive CBA-guideline for grid development projects, which also addresses these principles (ENTSO-E, 2013).

The method for this analysis is simplified. In context of reliability, the value of lost load can be compared to the cost of the backup technologies. As the value of lost load is ranked high (e.g. 10 000 EUR/MWh, (C. Batlle & Rodilla, 2010; Cramton, 2017)), the analysis focuses on the identification of a technology which serves energy in a reliable way at the lowest cost. Sustainability aspects are translated into costs to make the technological options comparable in a quantitative way. For instance, the pollution by emissions is priced for its environmental impact by the emission trading scheme (ETS).

Some indicators, such as the cost development of new technologies, the development of fuel and electricity costs, are subject to uncertainty. Their impact on the outcome is evaluated by sensitivities.

In the following, a criteria set for the evaluation of backup is established, suitable technologies are screened according to their eligibility for being a backup technology and evaluated based on the criteria set. The evaluation results of the single criteria are monetized and bundled in a cost comparison in the final step. In conclusion, the most cost-efficient technology for different levels of requested backup power is presented.

3.1 Criteria Set

The subordinate criteria, reliability, economic efficiency, and sustainability can be further specified. The established set of criteria is based on (Cebulla, 2017; Cebulla, Naegler, & Pohl, 2017; Nguyen, Martin, Malmquist, & Silva, 2017; Sterner & Stadler, 2014; Zapf, 2017) and illustrated in figure 2.

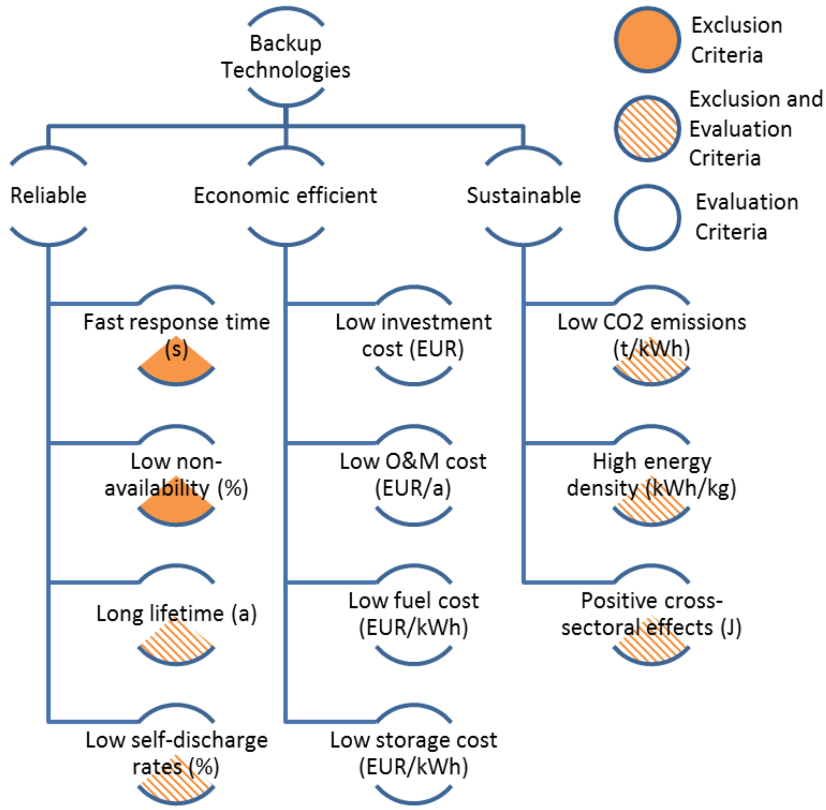

Figure 2: Criteria set for technology analysis

The orange marked criteria are only used as exclusion criteria for the screening of the technologies. Apart from the criteria for economic efficiency[3], every technology needs to fulfill a basic level of each criterion to be considered as backup technology.

Criteria for Reliability

Reliability is the main criterion for backup technologies. In case of scarcity, they need to be available fast and on a reliable basis. The **response time** for backup technologies can be compared to ancillary services, as they also need to balance the system. They range from 15 minutes to seconds (source). Looking at the reliability over a longer time span, the **planned and unplanned non-availability rates** of the technologies indicate how often the plant needs to shut down for e.g. maintenance or unplanned outages (source Paulus).

The technologies cannot exceed a certain level of response time and non-availability rates without harming the security of supply. Therefore, both aspects are used as exclusion criteria.

The other aspects are used as evaluation criteria as well. The degree of certainty is connected to **the lifetime and self-discharge rates** for storages. For some storage technologies, the stored energy

[3] Too expensive technologies are badly ranked in the costs comparison and are excluded automatically. As every criterion is translated into a monetary indicator, the exclusion of technologies based on sustainability and reliability aspects could be done through a bad rating of the criterion in the final costs comparison. As this approach would lead to a broad and confusing evaluation with additional benefit, the screening is executed as an intermediary step.

decreases during the storing time. These storages are not suitable to bridge the seasonal difference. Looking at the larger time scale, the longer the **lifetime** the more likely it is that the technology is available when it is needed. Frequent replacements disrupt the availability.

Criteria for Sustainability

A commonly used criterion for sustainability is the **emission of CO_2**[4]. To mitigate the global warming, the German government decided to reduce their emissions by 55 percent[5] for 2030. An indirectly impacting criterion is the energy density of the technology. If a technology has a higher **energy density**, less land and rare resources need to be used for its installation. Therefore, the impact on the environment is smaller (Sumper, 2016).

By providing electricity, some technologies offer energy for transport or heating as well. As the Dunkelflaute tend to occur during the cold time of the year, the covering of heat demand needs is a key challenge. Even though **positive cross-sectoral effects** help to replace other polluting applications for heating and transport, they are not considered as the analysis focuses on electricity applications.

Criteria for Economic Efficiency

In general, the costs can be differentiated between one time fixed costs and utilization dependent variable costs. The main part of the fixed costs is usually **investment costs**, which are the money spent to build a new unit or retrofit an existing one. They include installations for electrification and in case of some storage technologies separate entities for the transformation of electricity into another medium and storing (e.g. for power-to-gas, the electrolyzer and salt caverns). The main part of the variable costs is **fuel costs** in case of the power plants and electricity costs in case of the storages. The **costs for operation and maintenance** (O&M) are partly fixed costs and these are presented in Euro per year in this case (e.g. salary of the employees at the site). Other O&M costs are variable costs and are presented in Euro per kilowatt hour (kWh) (e.g. lubricants of the power plant).

The **technical efficiency** influences the variable costs. A lower efficiency needs to be compensated by a higher usage of fuel and more stored energy to offer the same level of backup energy. Therefore, efficiency is not used as a separate criterion but considered at the fuel costs and storage costs.

Another criterion, which influences the costs indirectly, is the depth of discharge. Some technologies (e.g. battery storage) are obliged to not discharge a certain minimum volume of stored energy. This needs to be compensated by higher investments.

3.2 Categorization and Selection of Backup Technologies

A variety of backup technologies exists. They can impact the supply and demand side. Gas power plants are an example on the supply side and an aluminum producer, which shuts down its facility in times of scarcity, on the demand side. A form which involves both sides are storages. According to (Sterner & Stadler, 2014), a storage involves three steps, the charging, the storing and the discharging. Some storages spread these steps over different sectors and commodity. For instance, electrical heating charges

[4] Other emissions are relevant for pollution but are not considered in the course of this thesis.

[5] Compared to the level of 1990

electricity but offers the charged energy it in form of heating (Sterner & Stadler, 2014; Sterner, Thema, & Eckert, 2014). In this analysis, only electricity-to-electricity applications are considered.

As depicted in figure 3, the underlying physical principles are another categorization of storages: Electrical (e.g. capacitor), electrochemical (e.g. battery storage), chemical (e.g. power-to-gas), mechanic (e.g. pump storage) and thermic storages exist (e.g. heat accumulators) (Sterner & Stadler, 2014).

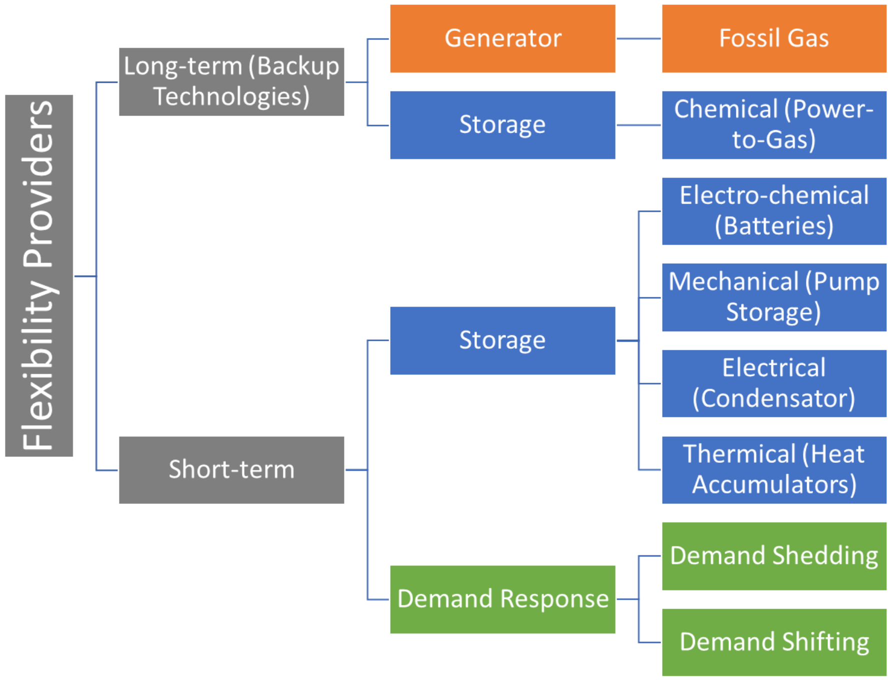

Figure 3: Overview of flexibility providers

The categories already give an idea of the variety of backup technologies. The availability of flexibility providers is a key requirement for backup technologies. As long as the fuel is supplied, and the requirements of operation and maintenance are met, a sufficiently long availability from the generators can be assumed. This is different for the storage and demand response.

Consumers can only shift or shed their consumption for a limited amount of time. For instance, cross-sectorial applications (e.g. air condition) can be max. shifted for 2 hours, production steps for 3 hours (Geipel, 2016) and the shedding instead of shifting the production steps is also limited to max. 4 hours (Klobasa, 2007)[6].

In terms of storage, the time of the discharging (also called energy-to-power ratio) and the duration of storing indicate the availability. On the one hand, the short discharging duration can be partly compensated by a higher amount of installed capacity, which is used consecutively (Cebulla, 2017). This approach can be limited by a lacking profitability or geographical constraints (e.g. suitable sites for pump storage). On the other hand, the duration of storing differentiates between short-term- and long-term

[6] In the extreme case of the California energy crisis, production sides shed their load for an even longer duration.

storage. According to (Sterner & Stadler, 2014), short-term storages stores for seconds, minutes, hours or days, whereas long-term memory is weekly, monthly or seasonal storages.

The thesis focuses on long-term backup technologies which are able to bridge the Dunkelflaute. Short-term flexibility is considered in the simulation as well to demonstrate its effect on the cost recovery of long-term backup technologies.

Some backup technologies are excluded from the analysis. Those are technologies with a small energy density (e.g. flywheel storage), geographical limitations (e.g. pump storage) and a restricted storing time (e.g. battery storage). The usability during the indicated lifetime is at risk for immature technologies. Therefore, technologies without a sufficient amount of prototypes (e.g. adiabatic compressed air storage) are ignored. On the other hand, highly polluting ones are not considered to be in line with the decarbonization goals of the German government (e.g. oil power plant).

As the analysis focus on the electricity wholesale market, another excluded category is technologies, which do not serve electricity but another commodity (heating, transport). Last but not least, backup technologies need to be available within minutes and have a low non-availability rate. For instance, lignite and coal power plants need up to 10 hours for ramping at a cold start (Buttler, Hentschel, Kahlert, & Angerer, 2015). Therefore, they could not be used in time to cover a Dunkelflaute and are excluded. Additionally, their non-availability rate is also almost two times higher than for gas applications (Paulus & Grave, 2012).

3.3 Description of Selected Backup Technologies

The selection results in the evaluation of fossil gas, biogas and power-to-gas applications, which are summarized by the term chemical storages (Sauer, 2016).

Chemical storages without and with conversion exist. The ones with conversion can use the inexpensive excess[7] energy to execute a chemical reaction. The resulting gas can be processed further, stored and transformed into electricity again. Typical examples are the power-to-hydrogen and power-to-methane technologies. Alternatively, technologies without conversion use gas from natural reservoirs or resources, such as fossil gas and biogas.

The technologies with and without conversion vary in their technological maturity and their cost structure. The power-to-gas technologies are still a subject of research, whereas gas power plants are commercially used for decades (Tomschi, 2013; Zapf, 2017). Looking at the costs breakdown of these technologies, the massive investments into the transformation and storage equipment lead to a fixed costs dominance for power-to-gas, whereas the main costs position for the gas power plants is fuel costs (Zapf, 2017).

The value chain of the gas applications range from gas exploration to electrification and cogeneration and is described in figure 4.

[7] Colloquial term – residual energy after the demand has been covered

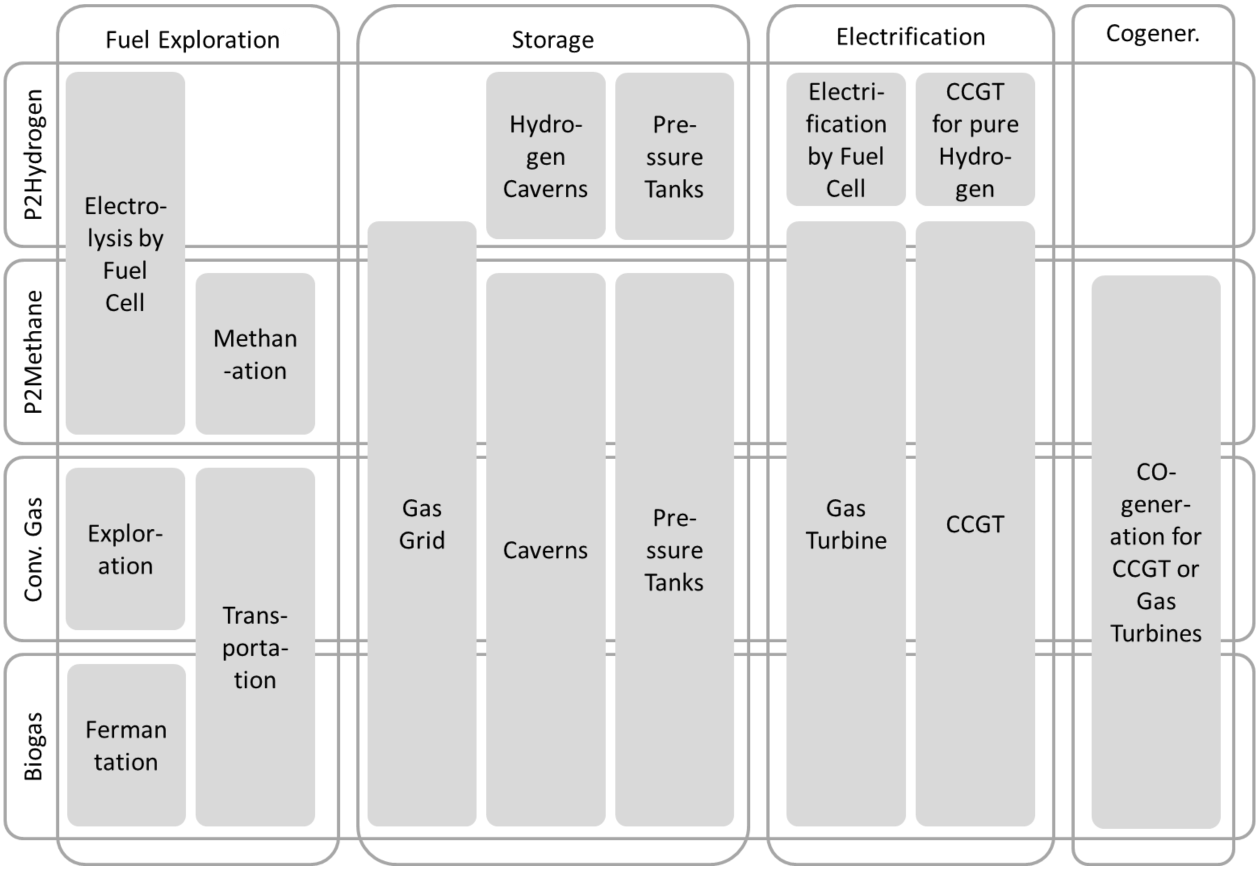

Figure 4: Value Chain of power-to-gas, fossil gas and biogas applications

Conversion Technologies

For the **fuel exploration** of power-to-gas, the conversion of water to hydrogen is done by the electrolysis in the first step. The process is comparable to a fuel cell but with the inverse current flow (Cebulla, 2017). The most common electrolyzers are based on alkaline or polymer electrolyte membranes (Cebulla, 2017).

With the help of the Sabatier Reaction, the hydrogen can be converted into synthetic methane by adding CO or CO_2 (Cebulla, 2017).

For the **storing** of the produced gas, different options exist. The German gas grid with its 23 billion cubic meters can be seen as the largest storage in Germany (Klinski, 2006). The storing of methane in the grid is possible to a large extent, as long as it fulfills its quality standards. Only the storing of hydrogen is restricted. The grid equipment is designed to handle a limited amount[8] of the highly reactive substance (Landinger, Bünger, Raksha, Weindorf, Simón, et al., 2014; Michalski et al., 2017). Alternatively, hydrogen can be stored in caverns or pore storages. Whereas pore storages are only suitable for seasonal imbalances, salt caverns can react flexibly to daily imbalances as well (Zapf, 2017).

Whereas the methane can be **electrified** in the same way like for fossil gas, hydrogen can be only co-fired with methane. Fuel cells enable the use of pure hydrogen and electrify via a chemical reaction with oxygen. Especially designed turbines for a high degree of co-firing and large-scale fuel cells are still a

[8] Currently 10% in Germany

subject of research (Cebulla, 2017; Landinger, Bünger, Raksha, Weindorf, Simón, et al., 2014; Sumper, 2016).

Technologies without conversion

Looking at the **exploration** of the used fossil gas, the majority comes from reservoirs outside of Germany. In 2015, 40 percent came from natural reservoirs from Russia, 21 percent from Norway, 29 percent from the Netherlands and only 7 percent from Germany (BDEW, 2016). In contrast to that, biogas is locally produced gas based on biomass (e.g. food stock, organic waste). The material is fermented, directly used at a cogeneration unit or further processed and inserted in the gas grid. Gas needs to be compatible with the requirements of the German gas and water association, DVGW, the German energy industry law, EnWG, and gas network access regulation, GasNZV (Klinski, 2006).

Even though other storing options exist like for the synthetic gas, the gas grid is the main storage medium as one large **storage** (Zapf, 2017).

The gas turbine, in which the gas is **electrified**, can be used solely, in combination with a steam turbine (combined cycle gas turbines, short CCGT) or in combination with cogeneration facilities. The use of waste heat for the heating or further electrification increases the efficiency of the power plant, but also the investment costs. The potential of cogeneration is explained in the evaluation section under the criterion "cross-sectoral effects".

3.4 Evaluation

Lifetime

The lifetime correlates with their technological maturity and complexity. For gas turbines and CCGT, they can be preserved for ca. 30 years (Tomschi, 2013). For biogas units, 20 years are the average lifetime (Kost & Schlegl, 2018), for the power-to-gas technologies, it is 15 years. As both technologies are still a matter of research, the information is uncertain. Especially the membranes of the electrolyzer are fragile and could be replaced more often (Cebulla, 2017) (see figure 5).

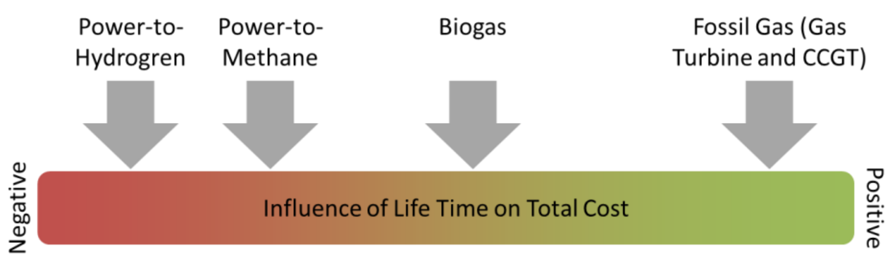

Figure 5: Ranking of life time

Self-discharge rates

Self-discharge rates are a bottleneck when it comes to battery storage. For synthetic gas, biogas and fossil gas applications, they are marginal and can be neglected (Zapf, 2017) (see figure 6).

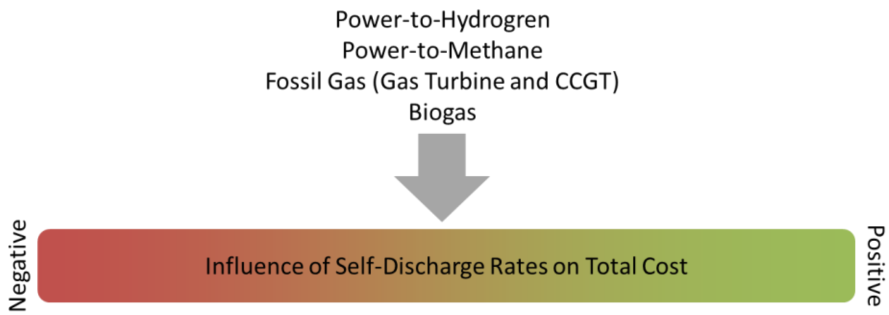

Figure 6: Ranking of self-discharge rates

CO_2 emissions

Combusting gas emits CO_2. A higher efficiency of the technology can improve the specific CO_2 emissions per kWh. The CO_2 emissions by the thermal gas power plant range between 520 and 610 g/kWh, whereas the more efficient CCGT are between 420 and 520 g/kWh (Luebbert, 2007; Milojcic & Dyllong, 2016). Coproduction can reduce the specific CO_2 emission even further. The amount of emitted CO_2 decreases on average by ca. 10 percent, if coproduction is added (Luebbert, 2007).

As biogas is mostly used with cogeneration, most resources report the CO_2 emissions in the context of it. Looking at the entire value chain of biogas including the cultivation of substrate, the fermentation, and the electrification, ca. 680 g CO_2 are emitted for every kWh (Luebbert, 2007). The production of the substrate is the most CO_2 emission intense step along the value chain. Therefore, the mix of substrates has a great impact on the CO_2 emissions (Szabó et al., 2014). The presented numbers are based on the current German biogas mix. The majority of biogas is based on food stock such as corn and wheat, whose production is highly CO_2 intense. Manure and organic waste are rated as emission-free but only account for a maximum of 14 percent of the substrate usage (BDEW, 2015; Klinski, 2006).

Two aspects relativize this high factor. First, no solid database can be derived from the limited number of biogas units. Secondly, not only the coproduction lowers the specific CO_2 emissions, but also the replaced technologies, which would emit more CO_2. Assuming biogas would replace e.g. highly polluting oil-fired heating, its CO_2 equivalent is significantly lower (Klinski, 2006).

These are some of the reasons why biogas does not need to cover its pollution with CO_2 certificates of the ECTS by the EU (Creutzig et al., 2015). Consequently, no costs for the CO_2 certificates are considered in the costs analysis.

The case of power-to-gas technologies is different. As the byproduct of the hydrogen reaction is water, it is considered as emission-free. The combusted synthetic methane emits CO_2 in a similar way as fossil gas, but the chemical reaction which transforms hydrogen into methane requires CO_2. This balancing counter effect makes it emission-free as well. The CO_2 from biogas unities or industrial processes can be used for this process step (Trost, Horn, Jentsch, & Sterner, 2012).

Not only the specific CO_2 emissions are relevant for the costs analysis, but also the price per ton of CO_2. Nowadays the CO_2 price is at a low level of ca. 5 Euro/t (Oei, 2016). (Oei, 2016) says that for a CO_2 price higher than 75 Euro/t the generation mix changes from a coal/lignite dominated mix to a gas dominated mix. To be in line with the German decarbonisation target (Oei, 2016; Pfluger et al., 2017), the CO_2 price of 75 Euro/t is used for the costs analysis (see figure 7).

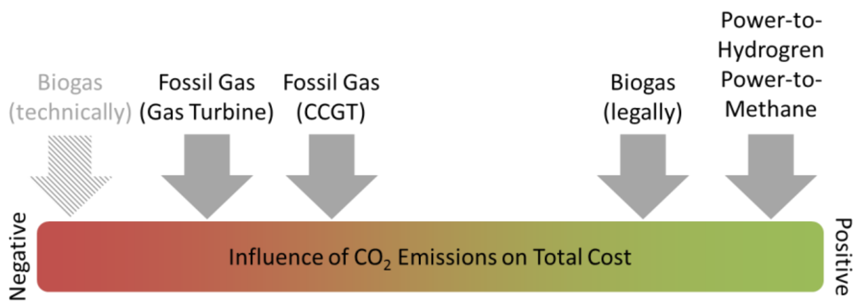

Figure 7: Ranking of CO_2 emissions

Energy density

The energy density can influence the design dimensions of the entity. To achieve a similar energy output, a larger entity needs to be installed for a technology with a lower density compared to a larger one. Also, technical difficulties to achieve a certain energy density need to be considered in this context. For instance, the ability of the storing facilities to create a certain level of pressure influence the energy density of hydrogen. In contrast to that, the energy density of methane is always higher than hydrogen (ca. three times) (Bossel, 2006). Biogas has roughly half of the energy density compared to fossil gas (Greengas UK, 2017). The gas quality and its current conditions of the gas influence the energy density and makes it difficult to provide a generalized statement (see figure 8).

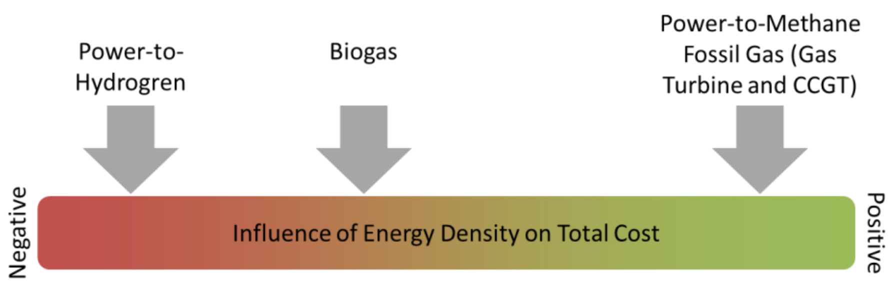

Figure 8: Ranking of energy density

Cross-sectoral effects

Looking at the potentials for cogeneration, the chemical reaction of the fuel cell creates no sufficient level of heat to use it. The heat of the gas turbine or CCGT can be used for district heating or other applications. Additionally, during the methanation process, heat occurs as a byproduct and can be used to produce steam for a steam turbine or nearby district heating (Götz, M., Lefebvre, J., Mörs, F., McDaniel Koch, A., Graf, F., Bajohr, S., Reimert, R., Kolb, 2016).

At the same time, a heat dependent production schedule limits the flexibility in case of electricity scarcity. In the worst-case moment of the Dunkelflaute, the request for electricity and heat coincidences. For other situations, cogeneration impedes the flexibility (Buttler et al., 2015) (see figure 9).

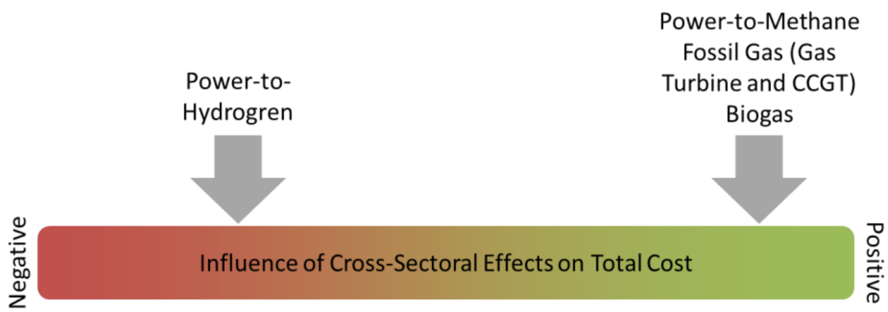

Figure 9: Ranking of cross-sectoral effects

Cost evaluation

All the evaluation criteria which are mentioned before are transformed into costs indicators and reflected in the cost evaluation. Before all the costs aspects are summarized in one calculation, the O&M, the fuel and investment costs are presented.

Most sources correlate the O&M costs with the investment costs (Landinger, Bünger, Raksha, Weindorf, Simón, et al., 2014; Zapf, 2017). The reason behind this is that more installed capacity or an increased complexity of the installation result in a more extensive operation and maintenance. It is similar for all technologies and ranges from two to four percent.

The investment costs are related to the technological maturity, its complexity, and efficiency. More efficient the technologies need less fuel to produce the same amount of electricity compared like less efficient technologies. For instance, with the efficiency of 38 percent for gas turbines and 60 percent for CCGT, the operator needs to insert ca. 10 TWh gas equivalent more in the gas turbine than in the CCGT to receive 10 TWh electricity.

In general, the fossil gas-based power plants have the lowest investment costs. A simple gas turbine costs on average 400 Euro per kWh and a CCGT 850 Euro per kWh. The fuel needs to be purchased from gas suppliers. This costs breakdown results in a low-costs basis, which is significantly increasing with the amount of produced electricity.

In contrast to that, the power-to-gas technologies use the inexpensive excess energy supplied by renewables. The operator can acquire the electricity via the wholesale market or bilateral contracts from the renewable operator. As the wholesale market prices need to be simulated for the first option, the underlying idea for the acquisition of the electricity is bilateral contracts in the calculation. The variable costs of the renewable power plant is used as the price of the bilateral contracts (Kost & Schlegl, 2018).

Nowadays, power-to-gas technologies are exempt from electricity taxes and network tariffs (Sailer, 2015). This constellation for the variable costs is used as one scenario for the costs analysis. Assuming that the exemptions like this are only temporarily offered to trigger investments, the reference case uses the same taxes and tariffs for all technologies.

A range of costs forecasts for power-to-gas exist. Looking at the production of the gas, the forecast of the specific investment costs for hydrogen range between 750 EUR/kW and 2.500 EUR/kW (Landinger, Bünger, Raksha, Weindorf, Bolwig, et al., 2014; Sailer, 2015; Zapf, 2017) and for methane between 900 EUR/kW and 1.800 EUR/kW (Pape, 2014; Sterner & Stadler, 2014; Trost et al., 2012; Zapf, 2017). Neglecting the numbers provided by industry associations lower as they might be biased, the average value of 1.200 EUR/kW for power-to-hydrogen and 1800 EUR/kW for power-to-methane are used.

The electrification is another costs factor for power-to-gas. For methane, the combustion means are the same as for fossil fuel. For the electrification of hydrogen, fuel cells or especially designed hydrogen turbines are used. As no reliable costs forecasts for these special turbines exist, the analysis focuses on fuel cells. They are still a subject of research. The current investment costs are ca. 5.000 EUR/kW. A costs decrease to ca. 2.000 EUR/kW and in the best case even 1.500 EUR/kW is expected (Wendt, 2006). The high investment costs compared to the combustion means are matched with a high efficiency of ca. 90 percent.

Not only the specific costs per kW or kWh are key for the costs analysis, but also the dimensions of the components. As explained in the introduction of this chapter, the installed capacity of the electrolyzer depends on the electrifier (gas turbine, CCGT or fuel cell). Generally speaking, in a renewable dominated system the electrolyzer can transform inexpensive excess energy into gas during almost the entire year. So, the electrolysis can be dimensioned rather small. Only during the rare scarcity moments, the electrolysis needs to stop and the gas turbine or fuel cell needs to electrify the gas to electricity promptly. So, the gas turbine needs to be dimensioned rather large.

To determine the dimensions of the gas turbine and electrolyzer, the peak of the residual load and the maximum amount for the uncovered load per year from the literature review is used as a reference. Consequently, 60 GW of gas turbines or CCGT needs to be installed for the electrification.

The size of the electrolysis (and methanation for power-to-methane) is influenced by the efficiency of the turbine, the efficiency of the electrolyzer, the uncovered load and the number of hours with excess energy per year. The maximum uncovered load in the literature review is 23 TWh p.a. The number of hours depends on the weather and share of renewables. As the number of hours with excess energy is not given explicitly in the literature, an own analysis of the weather year and renewable mix which is used in the chapter about the simulation is executed. For a renewable share of 50 to 80 percent of the consumption and the different weather years, the number of hours with excess energy range from 10 to 40 percent of the total hours p.a. The number of excess hours is used as a sensitivity. The needed installed capacity for the electrolyzer depending on the number of excess hours and electrification means is illustrated in figure 10. The average for every electrification technology is used.

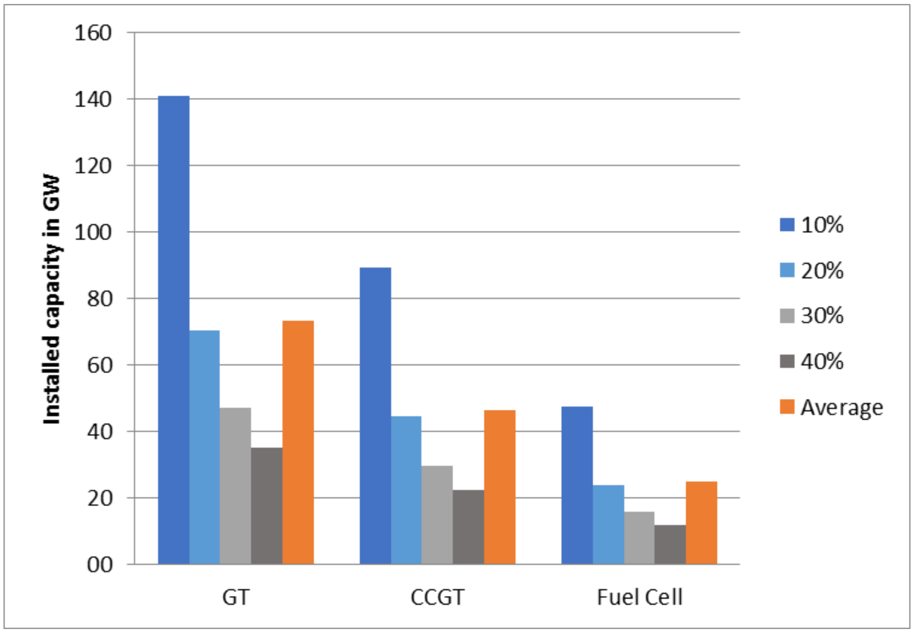

Figure 10: Technical dimensions for electrolyzer for different levels of excess energy (share per year)

Power-to-hydrogen is not only a special case in the context of electrification but also of storing. The fossil gas, synthetic methane, and biogas can be stored in the gas grid, if it fulfills its quality requirements (Cebulla, 2017; Klinski, 2006). As only a minor extent of hydrogen can be fed into the grid, salt caverns are the use case for storing in the calculation. For the investment costs, (Landinger, Bünger, Raksha, Weindorf, Bolwig, et al., 2014; Pape, 2014) states that they range between 1.400 and 1.850 EUR/kW. The variable costs are 11 EUR/kWh (Landinger, Bünger, Raksha, Weindorf, Bolwig, et al., 2014).

The composition of a biogas entity is rather complex. It includes a fermentation process, a processing of the gas to the quality standard of the grid, the transportation and the electrification. The limited amount of existing biogas entities and their different design makes it difficult to give generalized investment costs. (IRENA, 2015) indicated a costs variety of the components. (Kost & Schlegl, 2018) gives a range of 2.000 to 4.000 EUR/kW. (Ponitka et al., 2015) presents even higher specific investment costs for large-scale biogas (5250 EUR/kW). Therefore, the higher value by (Kost & Schlegl, 2018), 4000 Euro/kW is chosen. Substrate costs per kWh is added to the high investment costs.

Whereas the constellation of the units for biogas and fossil gas are already defined, a range of options is given for power-to-gas. For the power-to-hydrogen application, the electrolyzer is combined with a salt cavern storage and fuel cell. Similar as fossil gas, the synthetic methane is either combined with a gas turbine or CCGT. Co-firing of 10 percent hydrogen at a power-to-methane unit is analyzed as well.

The underlying costs assumptions of the reference scenario are changed for four alternative scenarios. In two scenarios, an unfavorable development of the power-to-gas costs is assumed. In “Base Price 2016 for electrolysis”, the power-to-gas applications do not get excess to the inexpensive excess power but need to pay the base price like nowadays. In “High investments for power-to-gas”, the investment costs of power-to-gas do not decrease as expected. The double amount of investment costs is assumed.

In the two other alternative scenarios, a costs constellation like nowadays is assumed. In “No network tariff for new technologies”, power-to-gas and biogas do not need to pay network tariffs for the usage of the gas grid. In “Low variable costs for fossil gas”, the lower price for fossil gas and CO_2 like nowadays are used (Oei, 2016; Tomschi, 2013).

All in all, eight different application cases are evaluated for five different scenarios (see figure 11).

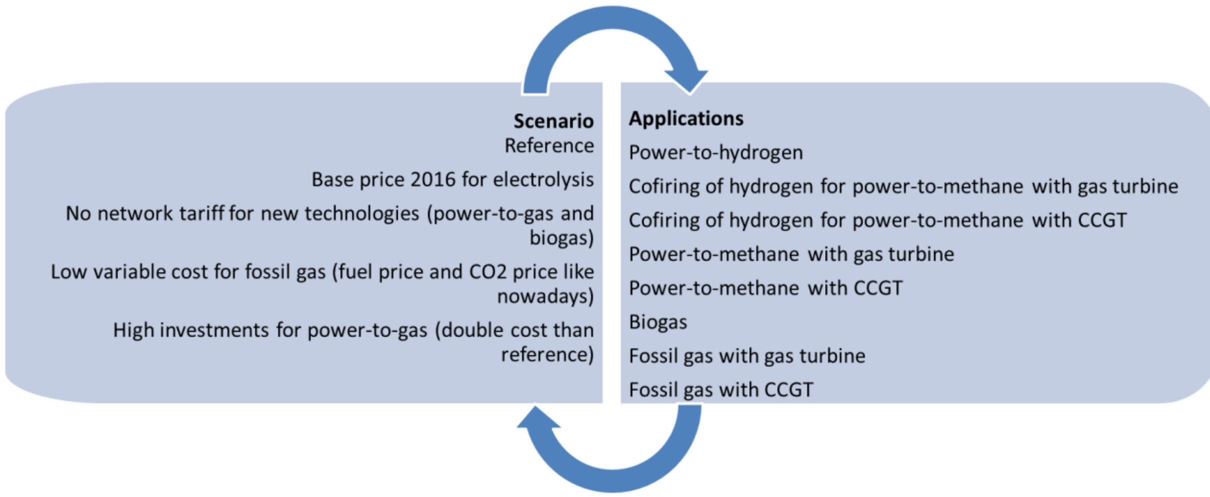

Figure 11: Scenarios and technological applications for cost evaluation

For the cost comparison, a fixed investment basis is matched with the scaled variable costs. Assuming a planning horizon of ten years and uncovered load ranging up to ca. 20 TWh per year, the analyzed TWh spectrum comes up to 200 TWh. Generally speaking, with a higher amount of requested energy a switch from variable costs dominated technologies to investment costs dominated technologies happens.

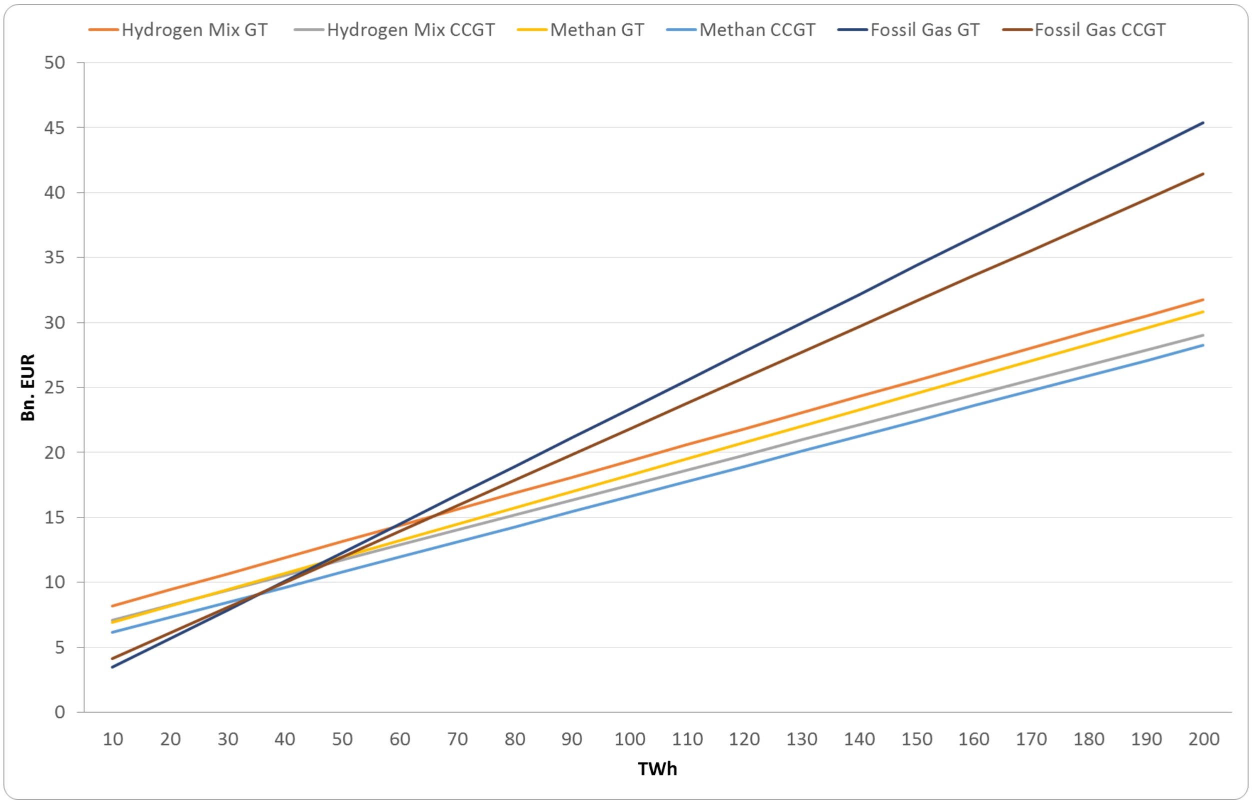

Figure 12: Total cost for backup technologies depending on the requested backup energy[9]

For the reference case, the following technology switch occurs (see figure 12): For a low amount of requested backup energy (up to 30 TWh), the fossil gas technologies are the most cost-efficient option. This is followed by power-to-methane in combination with a CCGT.

In the scenarios with higher investment costs for power-to-gas, the switch from fossil gas technologies to power-to-methane occurs at a higher level of produced energy (80 TWh). Higher variable costs for power-to-gas applications or lower variable costs for fossil gas application leads to an overall dominance of fossil gas applications. This can be seen in the scenarios "Base Price 2016 for electrolysis" and "Low variable costs for fossil fuel". On the other hand, exemptions from the network tariff for new technologies lead to an overall dominance of power-to-gas.

The most economically efficient technology in the different scenarios and the switch for the different levels of produced energy are depicted in figure 13. A concentration on the fossil fuel or methane application can be clearly seen. The total costs for CCGT is only slightly lower than the one for gas turbines.

[9] Biogas and the pure hydrogen application are not depicted in the figure due to a higher costs level

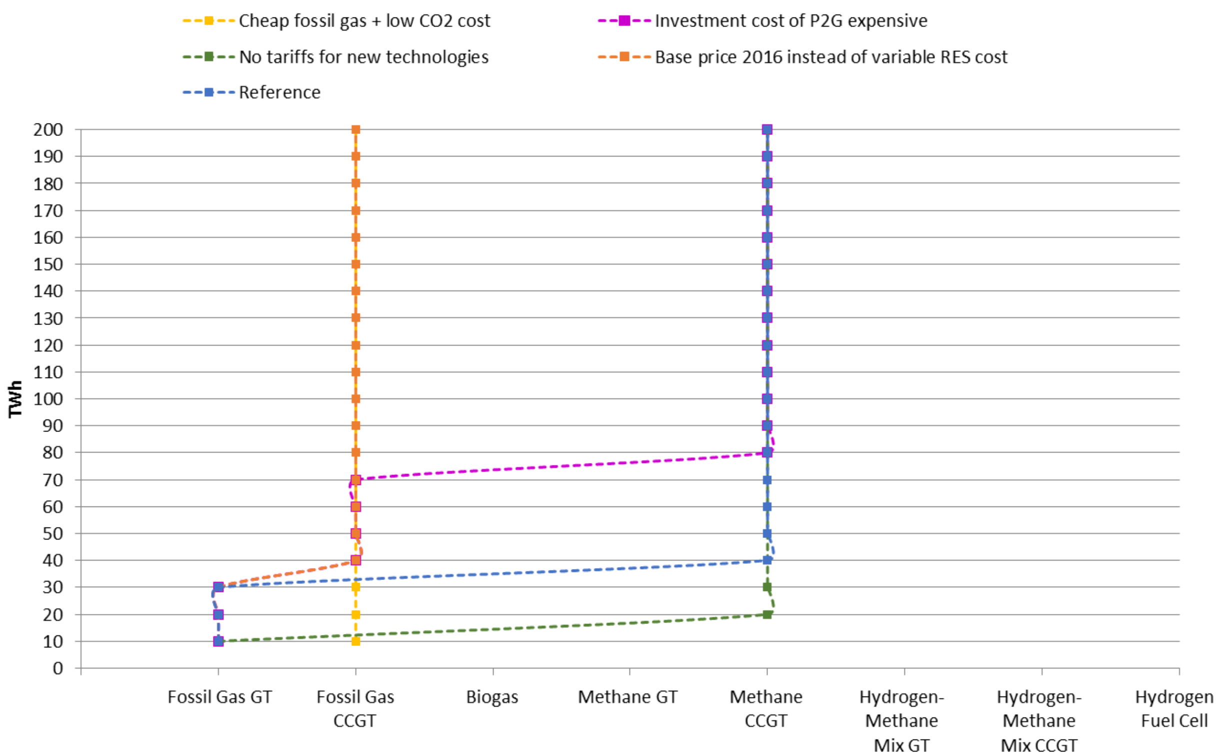

Figure 13: Overview of technology with the lowest costs for each scenario

3.5 Conclusion

In three of the five scenarios, power-to-methane is the preferred technology for a higher level of produced energy. Only if the variable costs for fossil gas applications remain at the same level as nowadays or if power-to-gas cannot make use of the inexpensive excess energy, gas turbines or CCGT with fossil gas are the more cost-efficient technology. As the uncertainty of future developments cannot be solved, both technologies are considered as backup technologies in the further analysis.

As the difference between the total costs of gas turbine and CCGT is marginal, but the reaction times of gas turbines are faster, the gas turbines are used for the simulation.

As a general finding of the cost evaluation, the fossil gas applications as variable costs dominated technology are better capable of handling changing request of backup energy. Therefore, they can be used as an interim solution in times of an unstable level of scarcity. As soon as a higher level of renewables provokes more hours of excess energy and a more constant level of scarcity over the years, the fossil gas can be replaced by synthetic methane provided by power-to-methane units.

4 The Multi-Criteria Decision Analysis of Capacity Mechanism

In the simulation of a renewable dominated power system by (Huneke et al., 2017), backup technologies account for 0.1 to 3 percent of the traded energy. The little and uncertain revenue flow involves the risk of investment restraints.

Instead of only pricing the sold electricity in the EoM, some countries start to price the service of capacity provision by capacity mechanisms (C. Batlle & Rodilla, 2010; G. Doorman et al., 2016; Van Der Burg & Whitley, 2016). Thereby, the rare and uncertain price peaks are not the only moments of cost recovery for the backup technologies but also extra payments organized by the system operator.

In case of a lacking cost recovery for backup technologies in the simulation, measures for an improvement of the cost recovery are presented and discussed in the last part of the thesis. For one measure, the simulated missing money of the backup is transferred in additional revenue streams of one selected capacity mechanism.

Different criteria about effectiveness and costs efficiency need to be considered for the selection of a capacity mechanism. To make them comparable, the mechanisms are ranked based on a criteria set. The different impact and importance of the criteria on the final outcome shall be reflected in the evaluation. A structured process for the creation of a criteria set and its weighting is captured by a multi-criteria decision analysis (MCDA) (J. J. Wang, Jing, Zhang, & Zhao, 2009). In the following a criteria set is established, the capacity mechanisms are selected, evaluated, weighted and compared. The highest ranked capacity mechanism is used as a measure for improving the cost recovery in chapter 10.

4.1 Criteria Set

The aim of the interventions is to create conditions under which investors are willing to invest into a sufficient level of backup capacity and maximize their output during a shortage to maintain the security of supply (Cramton, 2017; G. Doorman & Vries, 2017; Gawel, Korte, & Tews, 2015; Pérez-Arriaga, 2014). Uncertain investment conditions and a lacking cost recovery lead to investment restraints. The interventions aim to reduce the investment risk. The achievement of the aim of the intervention is described as **effectivity**.

The consumers as the main beneficiaries are the ones who are carrying the costs of the mechanism. As the system operator decides on their behalf, it is keen to prevent discontent and achieve the aim at low costs.

Whereas the effectivity is used as one criterium, **costs efficiency** is further specified. The capacity mechanism guarantees costs efficiency by triggering an efficient mix of backup technologies, minimizes the transaction costs and preventing overcapacity, inappropriately high capacity payments and disruptions of the EoM.

For the mix of backup technologies, static and dynamic efficiency needs to be considered. Whereas the static one refers to low prices at the current moment, the dynamic one refers to productive efficiency, which is provoked by higher sales and results in lower prices over the time (G. L. Doorman, 2000). Consequently, it is key to consider not only the most cost-efficient technology at the moment but in perspective as well. Following the principles of neo-classical economics (Pérez-Arriaga, 2014; Weintraub, 2017), market participants are in the best position to decide on most cost-efficient. Therefore, it is the role of the capacity mechanism to not limit the market participants in their decision and **not discriminate against** some flexibility providers, as long as the security of supply is maintained.

The total costs for the consumers are defined by the level of subsidized capacity and the level of payments. The provision of more backup capacity than needed to maintain the security of supply results in additional subsidy costs without any additional benefit for the consumers. The same effect applies for higher payments than needed to incite the sufficient level of investments. Therefore, another criterium for the efficiency of the capacity mechanism is the determination of an **appropriate level of total subsidy costs** (Buchholz, Karl, Pfeiffer, Pittel, & Triebwetter, 2012).

Last but not least, the processes of the mechanism aim to be efficient as well and result in a low level of transaction costs for the system operator, regulator and the participant (Buchholz et al., 2012; Williamson, 1987). The implementation and execution of the instrument should be in general **feasible and easy.** This involves one-time costs such as the adaptation of laws and processes and the reoccurring costs refer such as information gathering, the calibration of the parameters and the implementation of the processes (Buchholz et al., 2012).

The transaction costs also increase in the course of **adjustments of the instrument** and its payments. Unstable mechanisms **create additional risks for** the participants. This needs to be compensated by high **risk premium** for the investors (C. Batlle & Rodilla, 2010). Therefore, the design of the instrument aims to be robust.

According to (Carlos Batlle & Pérez-Arriaga, 2008; Pérez-Arriaga, 2014), the well-functioning market sends price signals on which the participants can decide to react and serves as an inherent control mechanism for cost-efficient behavior. This includes efficient investments. In this context, **price signals of the EoM** aim to be **not disrupted** by the instruments[10] (C. Batlle & Rodilla, 2010; Buchholz et al., 2012).

All in all, the selected instruments are likely to fulfill the aim of inciting investments, if they are designed in the right way. In this sense, the mandatory character makes effectivity to a less decisive criterion in this analysis. The more decisive arguments for the selection of the instruments are on the side of economic efficiency.

Not every criterium affects the overall costs in the same way. The weighting of the criteria according to their impact can be based on a reference case. Unfortunately, no detailed cost evaluations of existing capacity mechanisms are available. To get a rough idea about the share of the single costs elements on the total costs, the financial support of renewables is taken as a reference.

This intervention into the German electricity system imposes similar challenges like for the implementation of the capacity mechanism. In both cases, a technology which cannot recover its total costs in the market is subsidized and runs the risk of disrupting the EoM. Nevertheless, its differences need to be kept in mind. For instance, both technology groups have different cost structures and bidding patterns. Additionally, the merit order effect, which is mainly provoked by the low variable costs of the renewables, is different to the disruption by subsidized backup capacity (Van Mark, 2010).

Accepting these differences and taking the financial support of renewables only as an indication, the total costs overview created by (Van Mark, 2010) provide interesting insights. The subsidy costs itself is the

[10] A part from the scarcity prices

largest costs position directly followed by the distortive effects on the EoM. The most marginal costs position is the transaction costs.

Consequently, all the criteria apart from the transaction costs and the effectivity are weighted doubled.

4.2 Categorization and Selection of Capacity Mechanisms

A range of attributes describe the different capacity mechanisms. This includes, for instance, the subsidized product, the way to determine the subsidy, the eligible participants, the trigger for the activation of the backup capacity or the enforcement. The common aim leads to a similar design of some attributes. Before the individual mechanisms are described, their general nature is characterized.

General Nature of Instruments

The instruments are usually established by the system operator. The system operator ensures that the flexibility provider fulfills its duty. On the one hand, it defines preconditions to select the eligible flexibility providers. On the other hand, the measuring of provided energy in scarcity moments and a penalty for non-fulfillment are established to enforce the instrument (Buchholz et al., 2012).

The remunerated service and the structure of the remuneration are usually related to the provision of installed capacity. Similar to the pricing at balancing markets, not only the provided capacity in kW, but also the given energy in kWh can be remunerated to ensure the actual application of the installed capacity (Purkus et al., 2018). The level of the remuneration can be determined by competition (e.g. auction) or administration. For the activation of the provided energy, the EoM expresses scarcity in form of extreme prices. Therefore, an activation price for its activation can be determined or the system operator indicates the time of the activation. As security of supply is usually seen as a public good, the resulting costs are socialized. For some special instruments, the value of security of supply is monetized and the consumers need to decide on an individual basis how much they are willing to pay for this service.

Some aspects need to be specified further regardless of the design of the certain instruments, e.g. how to define an appropriate level of preconditions for the participation or penalties. This is subject of further research.

Selection of instruments

The BMWi started a discussion about the need for capacity mechanisms in Germany in 2014. As a follow-up of the consultation process about the future market design, a white paper was published, whose recommended measures aim to make the market more capable of handling renewables and enhancing flexibility. The fundamental question is whether the EoM triggers sufficient investments to maintain the security of supply. Thereby, the BMWi states a clear commitment to the EoM. According to their evaluation, the market needs to be further developed by accompanying measures. This concept is called EoM 2.0 and includes, for instance, higher penalties for imbalances (Lehmann, Gawel, Korte, Reeg, & Schober, 2016).

The BMWi sees no need for the introduction of a capacity market but considers the implementation of a strategic reserve (Lehmann et al., 2016). The foreseen gradual development of the market design by the

BMWi corresponds to the gradually increasing amount of renewables. In contrast to that, the thesis deals with a future scenario with a high share of renewables and a great need for flexibility. The effect of the single accompanying measures on the EoM cannot be evaluated in the course of the thesis. It is assumed that the radical scenario requires a comprehensive intervention. Therefore, the analysis focuses on centrally organized measures.

Whereas the BMWi only refers to the strategic reserve and the capacity market, the literature (e.g.(Betz, Cludius, & Riesz, 2015; G. Doorman et al., 2016; G. L. Doorman & Botterud, 2008; IEA, 2016; Van Der Burg & Whitley, 2016; Vazquez, Rivier, & Perez-Arriaga, 2002) discusses a range of capacity mechanisms. The following frequently mentioned ones are evaluated in the MCDA:

Capacity Payments - Strategic Reserve - Capacity Market - Reliability Contracts - Capacity Subscription

4.3 Evaluation

The evaluation of this chapter is based on the criteria set. Before the individual instruments are characterized, the correlation of the general attributes of the instruments and the criteria is analyzed.

The general correlation between general attributes and evaluation criteria

For most design options, a tradeoff between two or more criteria exist. For instance, if the preconditions for participation are too lax, the contribution of the remunerated flexibility providers cannot be ensured. But if it is too strict, some more cost-efficient options can be discriminated. The same issue was discussed in the course of the adaptation of the preconditions for the balancing market in Germany. For example, it was criticized that pooled entities and demand response are not accepted as flexibility providers and thereby economic efficient options are excluded (Purkus et al., 2018).

Whereas the appropriate level of preconditions cannot be addressed in the course of this thesis, one special aspect, the inclusion of the demand side, is taken into account. The demand and supply side face different challenges of being cost-efficient. Whereas the selection of the most cost-eficient technologies is key on the supply side, the demand side needs to be activated and become price-elastic first of all (C. Batlle & Rodilla, 2010).

In general, more setting parameters lead to a better fit and higher likeliness of achieving the final aim. On the other hand, the optimal calibration of more parameters also increases the transaction costs and makes the instruments more vulnerable for regulatory maladjustment (Buchholz et al., 2012; Van Der Burg & Whitley, 2016).

The time of activation is a subject of controversies as well. If it is activated, when scarcity already emerged, the demand is not properly protected from high scarcity prices. If it is activated at the small chance of a forecasted scarcity, the dispatch of the EoM would be disrupted frequently and the investment incentives via the price signal would be limited (Reeg & Kober, 2013).

In general, risk premiums are highly dependent on the expected revenue flow. For instance, the risk of a high penalty or uncertain level of remuneration will be reflected by an extra surcharge of the investors and increase the costs of the backup capacity. On the other hand, without penalties and a strict pricing, the system operator has no control to limit freeriding and other misbehavior by the participants.

An uncertain planning horizon does not only influence the level of the risk premium, but also the mix of backup technologies. According to (Ousman Abani, Hary, Rious, & Saguan, 2018), the operation and maintenance costs increase exponentially for power plants older than 10 years. Therefore, it would more costs effective to invest in a new power plant in most cases. But as this involves investment costs, which needs to be recovered over some decades, most risk-averse investors prefer to run the old power plants with higher operation and maintenance costs instead of taking the risk of not recovering the investment costs.

A key question about the market design and risk distribution is whether the risk shall be better assigned to the system operator or the market participant. On the one hand, a centralized monopolistic party can better absorb risks due to its size and the lower uncertainty. On the other hand, the market participants are more capable of finding efficient solutions to handle the risk (Ostrom, 2010). The underlying principles set the course for most interventions and cannot be addressed by this thesis due to time constraints.

Description and Evaluation of Selected Instruments

Capacity Payments (Buchholz et al., 2012; G. Doorman et al., 2016; P. L. Joskow, 2008; Lehmann et al., 2015)

For the majority of instruments, the needed installed capacity is defined and the price for this quantity is negotiated. For capacity payments, it is the other way around. The system operator determines the price per unit of installed capacity. The quantity depends on the participant's consideration whether the payment is sufficient for a certain amount of backup capacity. Contracted backup technologies interact in the wholesale market like other market participants and receive an extra payment. The extra payment supports their cost recovery. The payments can be fixed or dynamic. The latter means that they are adapted depending on the expected margin of the units. The costs are socialized. Whereas this approach is well suited for conventional power plants whose fixed costs need to be covered by their margin or an extra payment, it is not generally determined to which extent other flexibility providers (e.g. industries with demand response and storages) are eligible for the payment. Capacity payments exist in Italy, Spain, Argentina, Columbia, and Chile.

The indirect character of price-driven capacity mechanisms involves the risk of maladjustment (G. Doorman et al., 2016). For an accurate calibration of the payments, a range of empirical information and forecasts need to be gathered and evaluated. Whereas the preparation of the capacity payments is intense for the system operator, the later execution is simple. At the same time, the investment calculation can be based on an officially announced revenue stream of the capacity payments. This reduces the effort and risks for the participant.

The official announcement does not make the subsidy resistant towards adjustments and a dynamic environment with changing parameters (e.g. cost development of long-term storage). In this context, the balance between sufficiently high payments to ensure participation and a limited costs burden for the consumer is hard to meet. This imposes a risk, which the participant cannot impact.

As the main aim of a capacity mechanism is to ensure the security of supply, the system operator tends to tolerate a higher costs burden more than a lacking security of supply. The resulting high payments lead to high social costs.

Last but not least, the capacity payments involve not only risky side effects for participants, but also for other market players. Due to the additional payments, the subsidized participants can easily underbid other participants in the EoM. The suppliers with this extra payment have a competitive advantage compared to ones without (Buchholz et al., 2012). In case of a renewable dominated system, the other suppliers are reduced to a minimum and the problem is relativized.

Strategic Reserve (Betz et al., 2015; Bhagwat, Richstein, Chappin, & de Vries, 2016; G. Doorman et al., 2016; Joas & Küchler, 2015)

The strategic reserve is a targeted volume-based reserve acquired by the system operator (IEA, 2016). The power plants in this reserve are used in emergency cases. Most of the time, these targeted power plants are about to be decommissioned because of their lacking profitability. Due to their operational necessity for the system, they are transferred to a reserve. In case of small application pool for the strategic reserve, the compensation is usually negotiated on an individual level. A competitive determination of the premium is a rare case for a targeted instrument. As soon as the system operator activates the reserve, the market is frozen and the activation price is locked in as the price cap. The full costs of the reserve are covered by the system operator and are socialized later on. A strategic reserve is implemented in Germany and Sweden.

(Ousman Abani et al., 2018) analyses the impact of risk aversion on the scarcity for the different capacity mechanism by comparing two identical simulations once with risk neutral participants and once with risk-averse participants. In general, the risk-averse investors limit or delay their investments under uncertainty. According to (Ousman Abani et al., 2018), the exclusion from the EoM stresses the importance of cost recovery by the capacity mechanism. The unilateral revenue flow and the targeted quantity increase lead to a 0.2 percent increase in shortages compared to the risk neutral case.

Buchholz et al., 2012 argues from the standpoint of limited competition due to a targeted group of participants. In this situation, investment restraints or limited participation can increase the value for the backup technologies. To limit the concentration of power, (Buchholz et al., 2012) recommends the implementation of market-wide instruments[11].

Bhagwat et al., 2016 argues from a similar standpoint. His simulation points out the impact of the two main parameters of the strategic reserve, price and contracted quantity, on the utilization of the reserve. A higher volume prevents the abuse of market power and ensures the utilization of the reserve but to higher social costs and a reduction of the consumer welfare.

Looking at the potential market disruption, the determination of activation price is a sensitive topic. For instance, the low activation price for the Swedish strategic reserve is criticized for disrupting the market and impedes the dispatch of regular market participants. In the long-run, the restricted price signals limit the investments in the EoM. If the activation price is close to the price for non-served energy, the risk of disruption is minimal. As this price is practically hard to define, the strategic reserve with their centrally determined signal is vulnerable to market disruptions.

[11] even though they run the risk of given windfall profits to entities, which would not need a financial support of this level for avoiding their decommission

On the other hand, the simple design of the strategic reserve involves only limited effort for the system operator and risk of regulatory failure. For instance, no generalized procedure needs to be established for the individual negotiations.

Capacity Market (C. Batlle & Rodilla, 2010; Consentec, R2B, & Fraunhofer ISI, 2015; Cramton, 2017; G. Doorman et al., 2016; RtE, 2018)

In contrast to the strategic reserve and capacity payments, the capacity market is a market-wide approach, in which the needed capacity is auctioned and a price is determined based on it. Different forms exist. One main difference is whether the needed capacity is defined centrally by the system operator or decentrally by the individual consumers. In the auctions, the system operator or the consumer ask for secured capacity. This secured capacity is traded via capacity credits and involves the guarantee that this entity can provide electricity during scarcity times to the amount of contracted capacity. If the entity is not available during scarcity times or if the consumers did not purchase sufficient capacity credits in the decentral system to cover its consumption during scarcity times, they need to pay a penalty. The range of technologies which are allowed to participate depends on the preconditions of the market. For example, in PJM, one of the oldest and biggest capacity markets, demand response is also eligible for capacity credits and retailers offer cheaper tariffs, which includes the permission of temporary disconnection of the consumer.

Contracted backup technologies bid in the wholesale market like other participants but with the security of an extra payment. In the simulation by (Consentec et al., 2015), their additional revenue flow lowers the average wholesale and balancing price and increases the subsidy level for renewables. Although a lower market price seems advantageous for the consumers at the first glance, this intervention creates a less efficient dispatch and increases the total costs for the consumers in the end. This issue is prevalent for capacity payments and capacity market**.**

(Ousman Abani et al., 2018) analyses the impact of risk aversion on the scarcity for the different capacity mechanism by comparing two identical simulations once with risk neutral participants and once with risk-averse participants. The almost perfect fit of the targeted margin and flexible quantity of contracted reserves for the capacity market lead to a minimal increase of the shortages, which is less than 0,10 percent (Ousman Abani et al., 2018)[12].

Apart from the remuneration determination, (Ousman Abani et al., 2018) attests a low-risk potential for the participants. This statement should not cover up the complexity of the participation in an auction and the changing conditions of an auction over time.

Additional insights about the market participants and lessons learned about the operability of the mechanism are revealed gradually after some auctions. Therefore, more frequent adjustments tend to occur at the beginning after the implementation of the mechanism.

[12] the development of scarcity is based on extreme cases for the strategic reserve and capacity market. Whereas a level of competition and the static quantity of the strategic reserve result in a minimal margin for the participants, the auction of the capacity market lead to a perfect fit of the margin. Without knowing the single input parameters by (Ousman Abani et al., 2018) different conditions for both mechanisms would lead to a different outcome.

According to (Consentec et al., 2015), especially a capacity market with a centrally determined demand needs a high degree of information to create auctions which are resilient towards strategic bidding and deliberate investment restraints. For instance, the ex-ante definition of the auctioned capacity is based on forecasts and the information the market participant is obliged to provide. Unforeseeable developments and information asymmetry between participant and system operator can lead to miscalibration of the backup capacity level (G. Doorman et al., 2016). A mitigation of these risks requires additional expenses in better forecasts and more reporting. Another option to mitigate strategic behavior for central auction is the usage of a demand curve with a slope instead of a static one to determine the dispatch. Thereby, a higher price leads to a lower request for capacity (G. L. Doorman, 2005).

Another option to mitigate the risk of maladjustment of the requested backup capacity is to determine it on a decentral level. The consumers (or the retailers on behalf of the consumers) have better insights about their consumption and preferences than the regulator and a stronger incentive to reduce their costs. (IEA, 2016).The decentral approach is used by the decentral capacity market and the capacity subscription, whose structure is explained in the subsequent paragraph. Both mechanisms shift responsibility from the system operator to the consumer. This involves a higher effort for the consumer but has several other positive impacts in the context of costs efficiency.

First, decentral instruments incite a market-friendly behavior and thereby empower the EoM. Whereas central instruments aim to close the gap between demand and supply only by expanding the supply curve, the decentral ones consider the reduction of the demand curve. The improved elasticity raises efficiency potentials and impacts the EoM in a positive way.

Secondly, a self-rationing of the consumers and an elastic demand limit the risk of executing market power. Restrained capacity by other market players can lead to a higher capacity price. A natural control mechanism against this behavior is set in place if the consumers can decide between purchasing the capacity for a higher price or lowering their demand. Similar like for the sloping demand curve of the central capacity market, excessive capacity prices, and restrained investments tend to be avoided by it (Buchholz et al., 2012).

Instead of discriminating new flexibility providers, the decentral capacity mechanisms incite demand response. The broad consideration of flexibility providers leads to a more economically efficient costs mix of backup capacity. In contrast to that, the dominance of additional generation capacity from a central capacity market and reduced-price peaks even lead to a reduction of demand response of 4 GW by 2030 in the simulation of (Consentec et al., 2015).

Capacity Subscription (G. Doorman et al., 2016; G. L. Doorman, 2005; G. Doorman & Vries, 2017)

As mentioned in the previous paragraphs about the decentral capacity mechanisms, capacity subscriptions not only incite a system friendly behavior from the supply side but demand side as well. Like for the decentral capacity market, the need for capacity during scarcity hours for every consumer is defined. This depends on the correlation of the individual peak load and the system peak load. The obligation can be fulfilled by purchasing capacity credits or the curtailment of the individual peak load.

The capacity subscription assimilates the idea of involving the demand side, which is already applied to the decentral capacity market. The direct tradeoff between reducing the peak load and paying for secure capacity has additional benefits apart from the already mentioned ones in the previous chapter. It reinforces the individual value of security of supply. By this, the total costs are not simply socialized but transferred to the individual consumers depending on their preference towards an interruptible consumption.

As this instrument is not implemented so far, some questions according to the design remain open and impose uncertainties. For instance, the duration of the contracts between the consumer and the flexibility provider is a key design aspect of the effectiveness of the instrument. On the one hand, a short duration results in rather insecure revenue flows for the generator and limits its willingness to invest. On the other hand, long durations lock in the consumers and reduce the chance of a later flexibilization. In this context, a limited experience concerning the willingness for participation and the lacking infrastructure (e.g. smart meters for a remote curtailment of the consumption) complicate the implementation (G. Doorman et al., 2016; G. Doorman & Vries, 2017).

Reliability Contracts (Buchholz et al., 2012; Cramton, 2017; G. Doorman et al., 2016; Mastropietro, Batlle, Barroso, & Rodilla, 2014; Vazquez et al., 2002)

Reliability contracts and capacity subscriptions are newly designed approaches, which aim to simulate a system friendly behavior. Reliability contracts are similar to the financial product call option. In this case, the recipient of the service is the system operator and the traded good needs to be connected to a physical entity. As soon as a beforehand defined strike price is passed, the provider needs to pay the difference between the strike price and the market price to the recipient. For the recipient, it has the same effect as a price cap. The provider can counterbalance its financial loss by bidding at the market during these high prices (G. Doorman et al., 2016). Additionally, it receives a fixed payment for the provision of the service. In the short run, it is only an insurance against high prices for the consumer. In the long run, it aims to incite investments into technologies, which are able to bid during prices above the strike price.

For all mentioned capacity mechanism apart from the strategic reserve, a wholesale market-based and capacity mechanism-based component form the cost recovery. The special feature about the reliability contract is that its call option mechanism influences the revenue from the wholesale market. Missing participation during hours with prices above the strike price reduce its revenue. Therefore, it has an incentive to create own forecast about their expected contribution to system adequacy, revise their bidding strategy and behave in a more system friendly way. This self-responsibility leads to a high efficiency from several points of views but implies an uncertainty for the cost recovery. This could impact the willingness to invest and the effectivity (G. Doorman et al., 2016; Vazquez et al., 2002).

The strive for maximizing the income from the EoM prevents the abuse of market power. The providers harm themselves by provoking extreme prices in the market without bidding. Only the auctions for the reliability contracts are vulnerable to the abuse of market power (Buchholz et al., 2012).

The determination of the strike price for the reliability contract involves a similar difficulty like for the activation price of the strategic reserve. As the process of determining the strike price is made transparent by the auction, the auctioneer receives a direct feedback about the adequacy of the strike price in form of the offers. For instance, a high strike price is less likely to be activated and therefore more offers tend to lower the price of the contract. In this case, the low protection against scarcity and extreme prices is a sign for the system operator to reconsider the strike price.

Looking at the longer term, the reliability option incites investments into flexibility and reduces the scarcity. The decreasing level of scarcity results in the reduced need for protection against extreme prices. In this case, the contracted scarcity price increases gradually and makes itself after a while redundant, Thereby, the instrument is abolished without a disruption of the EoM (Buchholz et al., 2012).

Like explained for the other instruments, determining the appropriate level of reserve and controlling its enforcement is a challenge, which raises transaction costs. The enforcement and penalization are resolved by the design of the instrument. By no bidding during scarcity times, the participants reduce their income.

This inherent control mechanism addresses also one blind spot of most capacity mechanisms. Most capacity mechanisms focus on the provision of sufficient capacity but not sufficient electricity to cover the scarcity over a certain period. In the hindsight, missing electricity can be addressed by penalties for non-fulfillment. As providers of the reliability contracts need to create an elaborated bidding strategy to ensure income maximization, the need for the provision of sufficient electricity and for self-reliant forecasts is addressed from the start (Vazquez et al., 2002).

4.4 Conclusion

Looking at the appropriate level of subsidies and the needed capacity, the decentral instruments have a clear advantage over the central ones. The involvement of the demand facilitates the determination of the capacity demand and lowers the involved transaction costs on the side of the system operator. A lowering effect for the transaction costs is also given by strategic reserve and reliability contracts. As a targeted instrument, the transaction costs of the strategic reserve are relatively low. The absent necessity of an extra control mechanism reduces the expenditures for the reliability contract. Additionally, the reliability contract and the capacity subscription incite a system friendly behavior in line with the EoM. As depicted in figure 14, the capacity subscription fulfills the criteria in the overall evaluation in the best way.

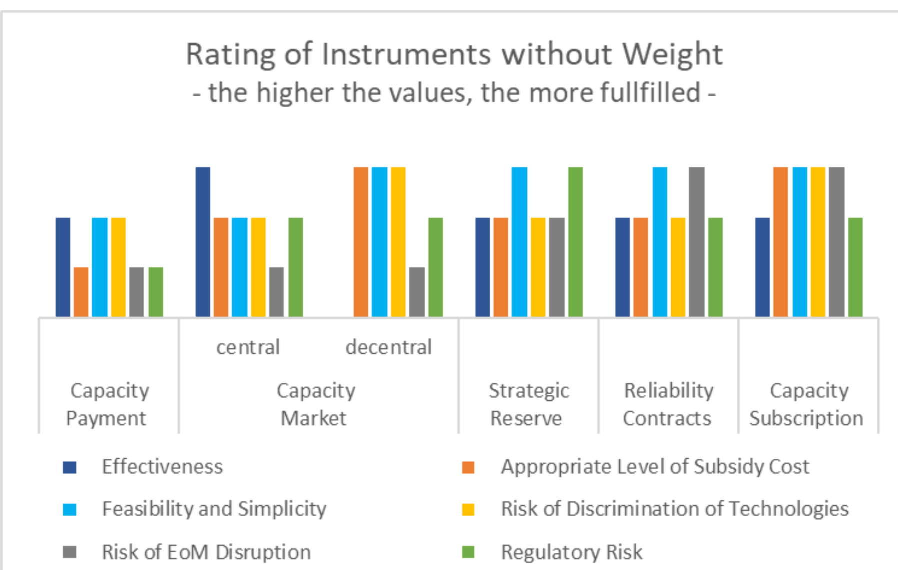

Figure 14: Rating of instruments without weight

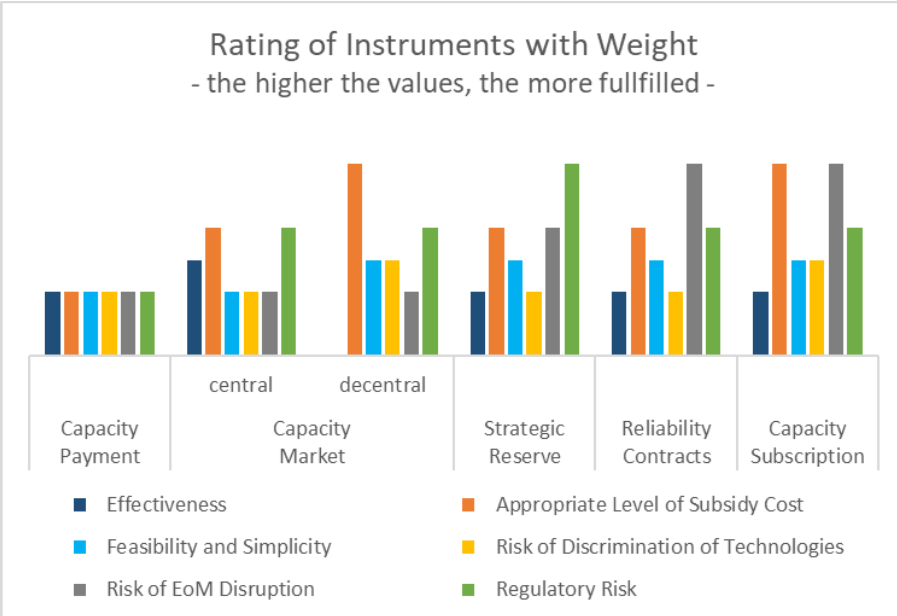

Figure 15: Rating of instruments with weight

If the all the other criteria apart from the effectivity and the transaction costs are weighted doubled, the results without weighting are intensified (see figure 15). The evaluation in favor of the capacity subscription and the limited fulfillment of the criteria by the capacity payment and central capacity market are stressed.

The result of the MCDA is a logical consequence of the advancement of capacity mechanisms. As a newly developed approach, the capacity subscription builds upon the drawbacks of the existing instruments. At the same time, the design of this instrument is not tested in reality so far. It leaves room for further interpretations, speculations and design recommendations. This situation is seized in the last part of the thesis. The effect of the self-rationing is demonstrated by the example of industrial consumers.

5 The Agent-Based Model AMIRIS

The scarcity shows different forms. A gap between supply and demand can occur extensively out of the sudden and lasts only for one hour or can be a consecutive scarcity period over some days. This depends on various parameters. Those are, for instance, the availability of the conventional power plants, the pattern of demand and the supply by weather-dependent renewables or the bids of the storage. To condense these parameters into one set of information, a model is used.

In the following, the requirements for the used energy dispatch model are described and the selected model is presented. Before the model is used in the subsequent chapter, it verified and validated. The verification shows that the model and its agents are doing what they are supposed to do. In other words, that the concept of the model is translated into the software correctly. On the other hand, validation checks whether the model is an adequate representation of the real world from the perspective of the intended application (Ormerod & Rosewell, 2009).

5.1 Reasons for the Selection of AMIRIS

Fernández-Blanco Carramolino et al., 2017 presents a list of model features which characterize power system models (see figure 16).

Model Feature	Attributes			
Analytical Approach	Top-Down	Bottom-Up	Hybrid	
Underlying Methodology	Optimisation	Simulation	Equilibrium	
Mathematical Approach	Agent-based Programming	Dynamic Programming	Mixed-integer Programming	Linear Programming
Uncertainty Handled by Modles	Fuel Price	Intermittent Generation	Load	Flexibility Provision
Time Horizon	Multiple Years	One Year	Moths	
Time Step	Yearly	Monthly	Daily	Hourly
Geographical Scope	Global	Regional	National	Local

Figure 16: Selection of model features for the analysis

Some required features for the modeling are directly given by the scope of the thesis. The impact of individual weather years and flexibility is analyzed on the spot market in Germany with an hourly resolution. Predefined extreme cases indicate the level of uncertainty, but the uncertainty itself is not a subject of the model.

The main model methodology aims the be a simulation to represent the conditions of an insufficient level of secured capacity. At the same time, single elements like the usage of the storage shall be optimized. Both requirements are addressed by the modular structure of the agent-based model.

The self-determined generation mix and especially the level of investment restraints is susceptible. A higher or lower level would lead to a different level of scarcity. On the one hand, it needs to be made explicit which results are only a consequence of the input parameters or generalizable finding. On the other hand, a sensitivity analysis demonstrates the impact of changes of the parameters.

Its modular structure which reflects on the behavioral decisions of the single actors results in a selection of the agent-based model AMIRIS developed by the German Aerospace Centre (DLR). In AMIRIS, the behavior of the agents can be influenced by the regulatory framework. In the case of a lacking cost recovery, the additional payments by a capacity mechanism could be implemented in AMIRIS and the changes in the behavior can be observed. Even though this investigation cannot be examined in this thesis due to time constraints, it can be used as preliminary work.

5.2 Model Overview

The decreasing dominance of a central planner or a few large market players in the power sector brings up new challenges and asks for different methods and models to evaluate them. The model developers of AMIRIS frame the new situation like this "The result of markets at the macro level of the system is based on a variety of individual actions on the micro level." (Deissenroth, Klein, Nienhaus, & Reeg, 2017). The uncertainty connected to the individual decisions of the market players is captured and explored by the agent-based model AMIRIS.

Nowadays, the individual decisions on the micro level are increasingly influenced by policy instruments. The acceptance of the instruments and their side effects can hardly be determined in advance. Chappin et al., 2017 describes several sources of complexity which underline the need for policy modeling and especially agent-based models. One presented aspect is the imperfect foresight of the behavior of heterogeneous actors, which is addressed by AMIRIS as well.

The development of AMIRIS in its current form started with a project in 2010 (Reeg et al., 2013). Recently, the merit order model was updated and a storage agent added. AMIRIS is in a mode of steady progress. To understand the potential of the model and its structure, the envisioned advancements are named, but only the used elements for the simulation are explained. It needs to be differentiated between the envisioned design of the model, the current design with its possibilities and the selected elements for the analysis.

As illustrated in figure 17, AMIRIS represents the actors which are interacting according to their coordination mechanisms in a techno-economic regime. Constraints or incentives from the regulatory framework guide their decisions.

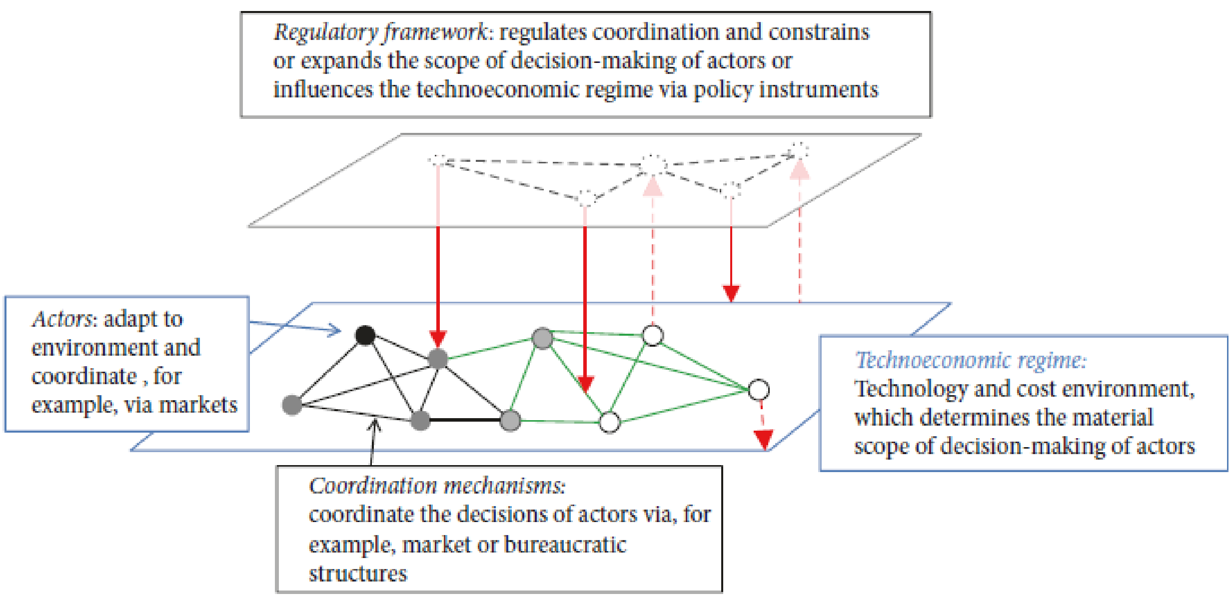

Figure 17: Conceptual approach by AMIRIS, source: Deissenroth, Klein, Nienhaus, & Reeg, 2017

The agent topology consists of three kinds of actors with the scope of decision making and five without (see figure 18). Within the simulation of AMIRIS, some actors are entitled to optimize themselves by making decisions. For instance, renewables are able to choose among power purchase offers from different traders (in the figure 18 called direct marketer). As the preferences and conditions of the actors in real life differ according to their ownership or technology mix, their attributes are further differentiated by types of actors. For instance, big utilities have a higher capital stock and return requirements than small municipal utilities (Deissenroth et al., 2017; Reeg et al., 2013).

The installed capacity of the generation mix is determined exogenously. It is derived from common literature or the evaluations by the linear optimization model ReMix developed by DLR. For ReMix, the data assessment is separated in a sub-model called EnDAT (Stetter, 2014). The provided data by EnDAT has a high spatial and timely resolution for Europe and is aggregated for the use in AMIRIS.

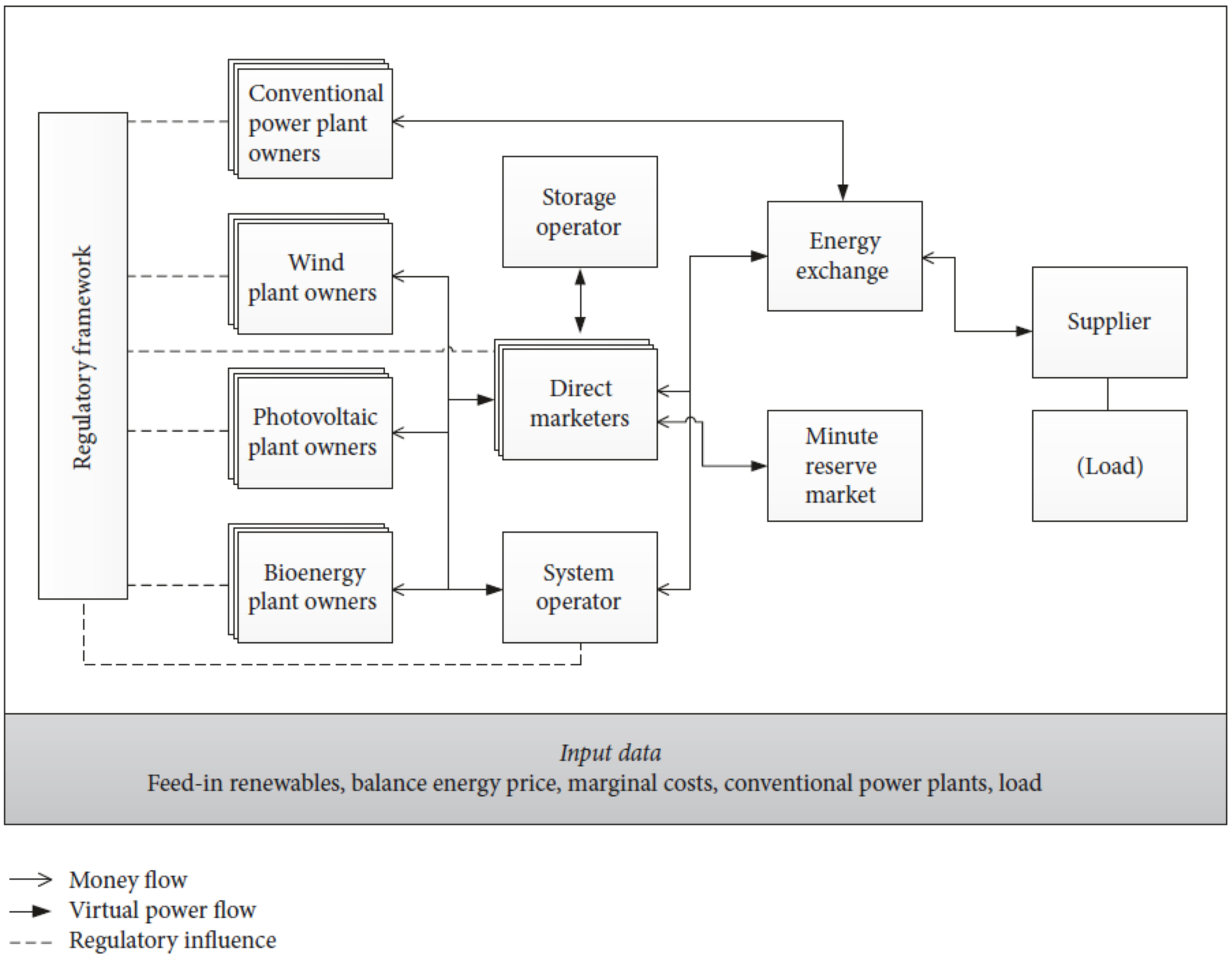

Figure 18: The AMIRIS model, source: Deissenroth et al., 2017

The utilization of the model for this thesis is simplified. The actors are only differentiated by their technology, not by their ownership. Every generator is linked to one trader. The renewable generators are assigned to a technology specific and fixed market premium. For the dispatchable generators, the trader creates the bid for the energy exchange based on the installed capacity, the variable costs, the availability and the technical efficiency. This information is provided by the generation agents. The installed capacity is divided by a predefined block size for every technology. The capacity of every block determines the quantity of the bids. As different technical efficiencies for one technology exist, a range of efficiencies is given, which is equally spread among the blocks.

For the non-dispatchable generators, no variable costs are assigned. The linked trader bases its bids on the installed capacity and the generation pattern determined by the technology specific and weather dependent time series. The bids by renewables only deviate from the generation pattern, if the trader foresees a market price which cannot be compensated by the market premium and initiates the curtailment of the photovoltaic or wind plants (Deissenroth et al., 2017).

It is possible to implement forecasting errors or other random factors in the behavior of the actors. This would lead to different outcomes for identical model runs. Due to time constraints, no forecasting errors are implemented and evaluated. Therefore, every run with the same input parameters lead to the same outcome and no experiment setup with repetitive runs is needed.

In the setup for the thesis, only the storage is entitled to optimize its bidding to maximize its profit. It capitalizes on the price spread by charging during low prices and discharging during high prices. The upcoming prices and underlying dispatch without the storage are given to the storage to select the most attractive hours for its bidding. Thereby, the storage not only knows on which price it can capitalize on but also how much energy it can bid without lowering the price. By this approach, the implementation of only one storage entity is possible so far. In a competitive environment for the storages, it is difficult to determine the optimal bidding strategy, as the prices depend on the unknown bids of the other storages.

The horizon of known future prices is limited by the defined foresight. Within one run, the model determines first the dispatch without the storage, aligns the bidding by the storage according to it and then simulates the dispatch with the storage. Due to the rolling horizon of the foresight, the storage is inactive in the first foresight period within the simulation time span. This period is not considered in the analysis. Additionally, the attributes of the storage are defined by the technical efficiency, its self-discharge rate, the energy-to-power ratio and the installed capacity (Schimeczek, Deissenroth, Fleischer, & Reeg, 2018).

The kind of actors without the scope of decision making are the negative minute reserve, the system operator, the energy exchange, the total load and the regulatory framework which determines the market premium for the renewables. The load is defined by the pattern of the hourly time series and the yearly consumption. No demand response is implemented. The energy exchange creates the merit order based on the bids by the traders, compares it to the demand and determines the price for every hour of the year. If the supply can cover the demand, the bid of the last dispatched power plant determines the price. If not, a scarcity price at the level of the price cap is used.

The analysis focuses on the energy exchange in a future system without the feed-in tariff. The negative minute reserve and the system operator which trades the renewable energy in a feed-in tariff system are not used. In case of the implementation of the minute reserve, the generator would receive an additional surcharge for the participation in the minute reserve by its trader.

The described model is utilized as described. No modifications of the model are developed and implemented within the thesis.

5.3 Verification

A concept for a model involves a range of elements which aim to perform a certain task to achieve its final aim. The ones which are most relevant for the subsequent simulation are verified in the following. The price formation, the challenge of maintaining the security of supply despite more frequent occurring extreme situations in the market and its mitigating mediums are key for the analysis. Therefore, those elements are selected for verification:

A. The correspondence of the market price to the marginal costs of the conventional power plants in case of no implemented storage
B. The correlation of the market price at the level of the price cap and uncovered load
C. The correlation of the negative prices and residual load
D. The bidding of the storage based on arbitrage

As explained in 1.2.3, the conventional power plants shall base their bid on marginal costs. Consequently, in a scenario without a storage, the prices shall reflect the marginal costs of the power plants. This relation can be observed in the comparison of the price duration curve in figure 20 and the marginal costs of the conventional power plants in figure 19. For each conventional technology, a range of technical efficiency is used determined by a technology-specific minimum and maximum value. The different efficiency levels are spread over the blocks of the different technologies. By this, gradually changing price level instead of a stepped price duration curve is created.

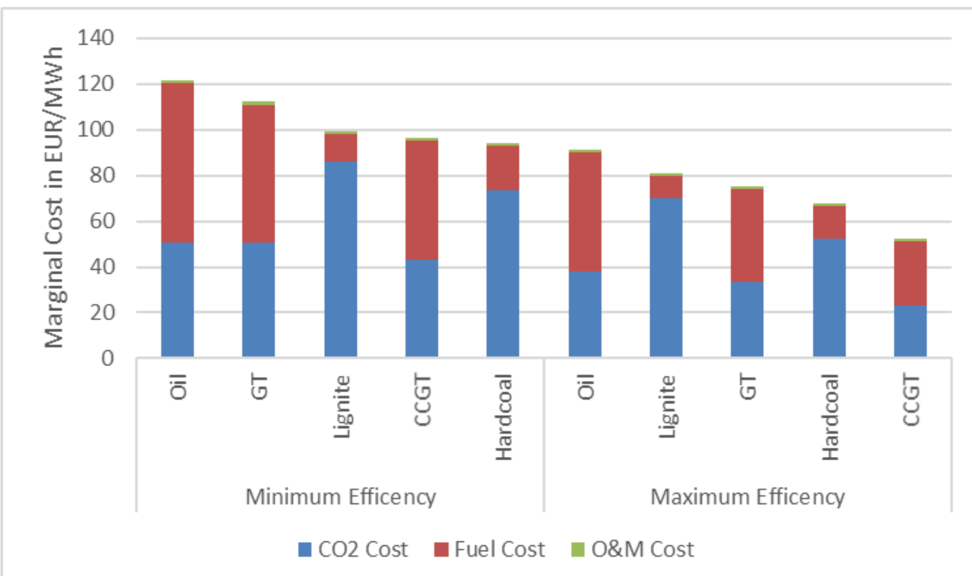

Figure 19: Conventional technologies ranked in order of their marginal costs

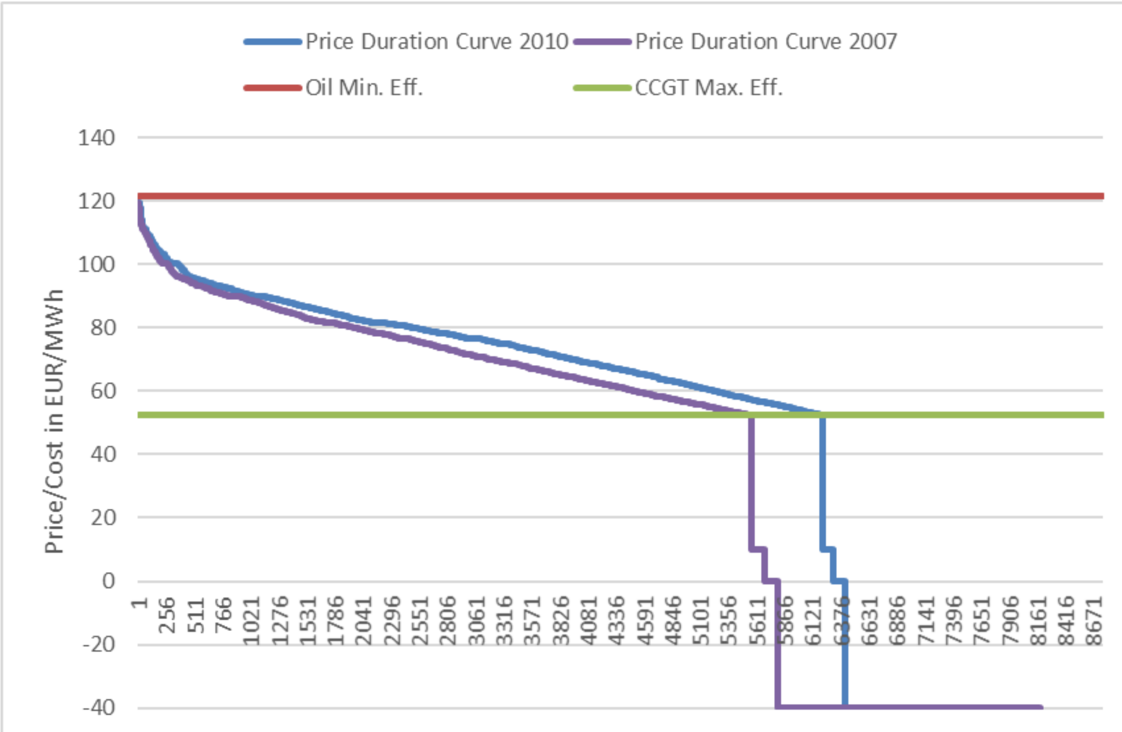

Figure 20: Price duration curves for the weather year 2007 and 2010 and the conventional technology with the highest and lowest marginal costs

The lower price than the least expensive conventional technology results from the small level of import with fixed costs of 10 EUR/MWh and the renewables.

If the load cannot be covered by the offered supply, the offered energy is dispatched for the price of non-served energy or the price cap (if implemented). In the energy exchange of AMIRIS, a price cap of 3000 EUR/MWh is implemented like in the German spot market nowadays (BMWi, 2018). For the correlation between the price of 3000 EUR/MWh and the uncovered load, constellations with different weather years, renewables shares, and levels of installed storage are tested. All constellations show a price of 3000 EUR/MWh for uncovered load and vice versa. Examples are plotted in figures 21, 22, and 23.

Figure 21: Correlation of price & uncovered load for a high share of renewables, no storage & an extreme weather year

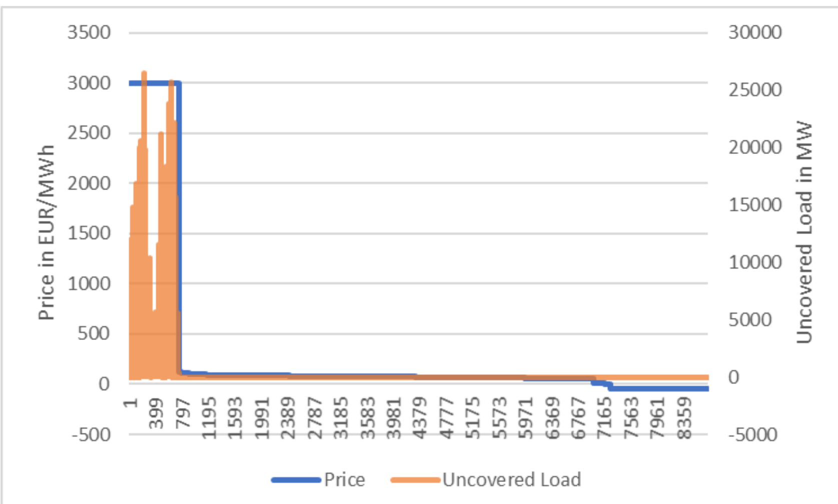

Figure 22: Correlation of price & uncovered load for a medium share of renewables, medium storages & extreme weather year

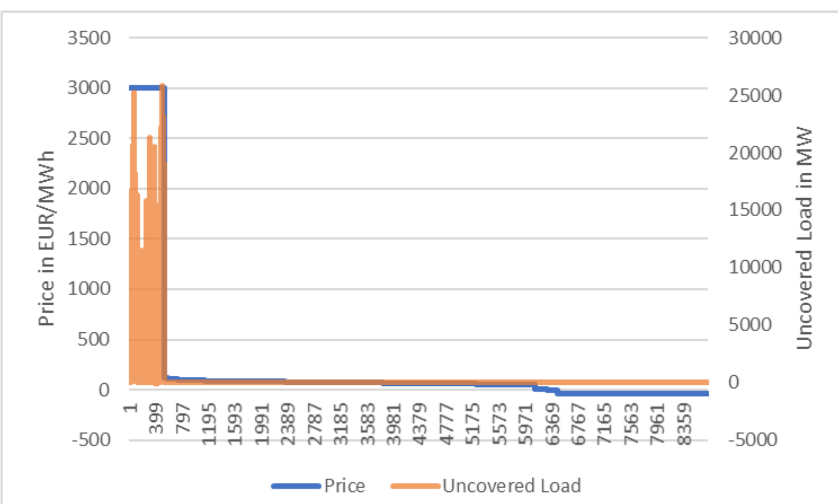

Figure 23: Correlation of price & uncovered load for a medium share of renewables, large storages & mild weather year

The price duration shows that no prices lower than -40 EUR/MWh occur. This is based on the requirement for the model that renewables shall be curtailed when their margin turns negative. The renewables are curtailed at a price level of -40 EUR/MWh, as the negative prices up to that level are still covered by the market premium.

The negative prices shall occur when more renewable energy is generated than demand is requested. In other words, when the residual load is negative. The correlation of negative prices and negative residual load is first tested for a generation mix without storage. For different weather years and renewable share, the correlation can be proved like in figure 24 illustrated.

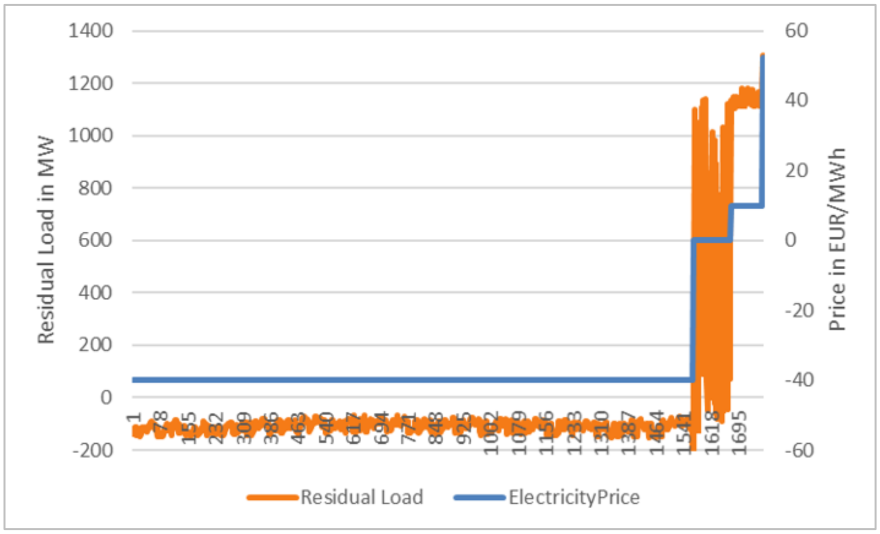

Figure 24: Correlation of residual load and negative electricity prices

The same comparison but with a storage gives an ambiguous picture. Different aspects need to be considered to understand the correlation between the residual load and prices. In hours of planned curtailment of renewables, the storage utilizes the curtailed energy. It also counterbalances an increase of the residual load by discharging. An example of this phenomenon is pictured in figure 25.

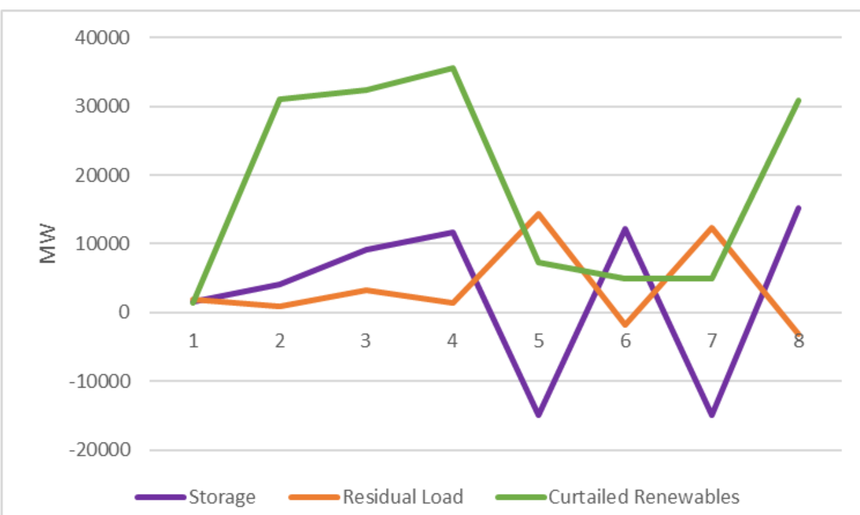

Figure 25: Example of the utilization of storage during negative prices (positive storage values express charging, vice versa)

The observed charging and discharging is connected to another distinctive feature of the storage behavior during negative prices. For positive prices, the storage loses money by purchasing and selling the energy at the same price due to its technical efficiency[13]. By purchasing energy during times of negative prices, the profit is increased. As energy is lost by the discharging, the storage decides to sell energy at negative prices to purchase more energy afterwards.

A detailed analysis and verification of both phenomena during negative prices is not possible due to time constraints. As the model fulfills its aim to create negative prices in times of a negative residual load without a storage and as the number of negative hours decreases with the emergence of storage, these two characteristics are accepted.

The general bidding pattern of storages in the energy exchange of AMIRIS is verified by (Schimeczek et al., 2018). In the project, the agent-based model AMIRIS is merged with the linear optimization model E2M2. Both models receive the same set of data and instructions and analyze the behavior of the flexibility providers biogas and storage. In the end, their outcomes are compared. The storages of both models show the same pattern of charging during low prices and discharging during high prices. The bidding scheme of the storage is hereby confirmed (Schimeczek et al., 2018).

5.4 Validation

A common approach for the validation of a dispatch model is the comparison of the historical prices and the modeled prices under the same historical conditions.

(Klein, 2018) validates the exchange model in AMIRIS by comparing the historic EEX prices in 2015 and 2016 with the simulated prices under the same conditions as in 2015 and 2016. The average price over the two years in AMIRIS is only 1.8 percent higher than the historical average price.

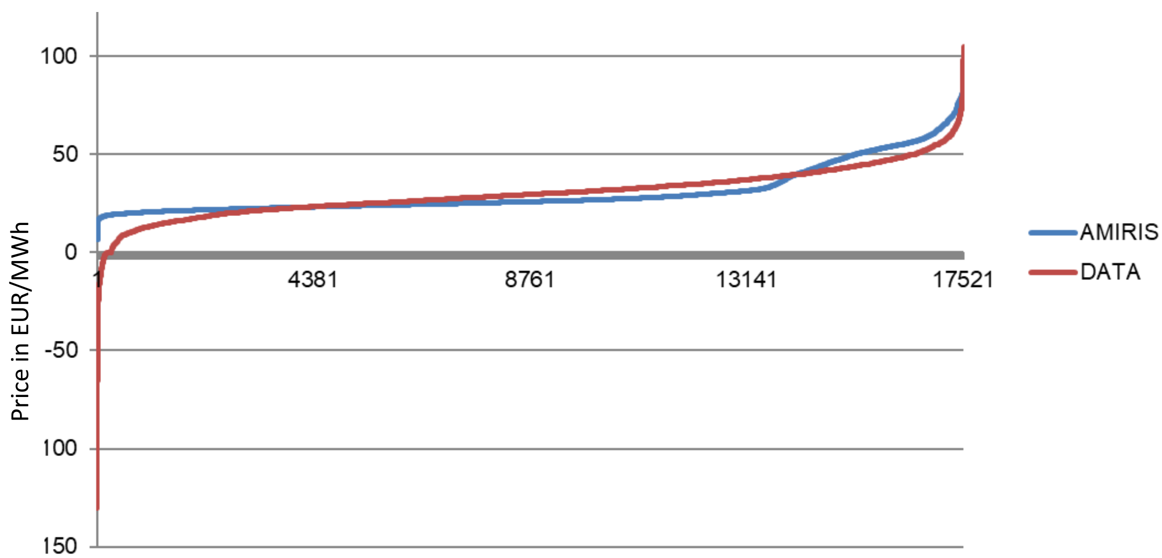

Figure 26: Price duration curve for the historic values of 2015 and 2016 and model results, source: Klein, 2018

[13] 99 percent in the simulation

The deviation for lower prices results from missing markups for the conventional power plants. Markups reflect adaptions of the bid based on marginal costs. For instance, conventional power plants can lower their bids to avoid the ramping down and up in case they are not dispatched for a single hour during a period of constant running. (Klein, 2018) creates markups with a genetic algorithm and demonstrates the better fit with the historic prices (compare figure 26 and figure 27).

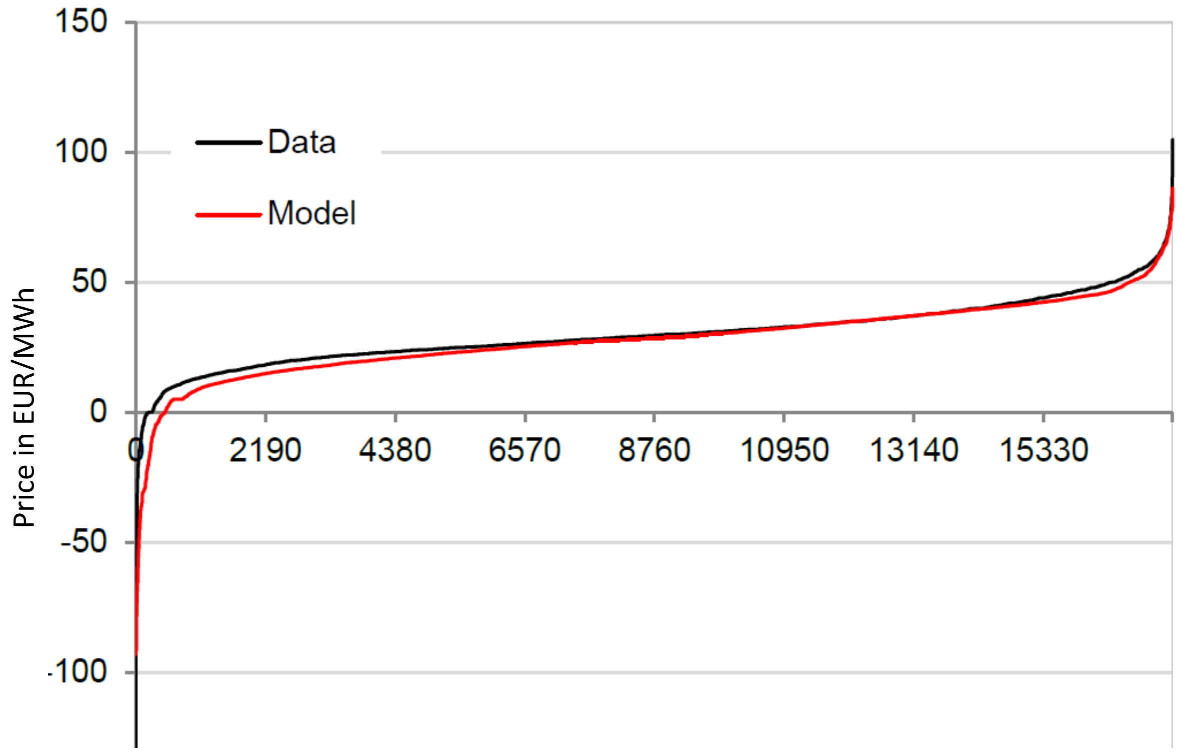

Figure 27: Price duration curve for the historic values of 2015 and 2016 and model results with markups, source: Klein, 2018

Markups depend on the circumstances of the generation mix. Therefore, new markups would need to be created for the simulation of a future scenario with less conventional power plants. The creation of own markups is not possible in the course of this thesis due to time constraints. The bids are based on marginal costs and the deviations for lower prices are accepted.

6 The Simulation Design

The in chapter 1 established hypotheses shape the investigations and especially the simulation:

> Hypothesis 1: Apart from fluctuating, weather-dependet renewables, other energy sources are needed as a backup to maintain the security of supply. The requested backup energy varies substantially with the weather conditions.

> Hypothesis 2: Short-term flexibility providers, such as battery storage, lower the need for backup capacity but cannot substitute it.

> Hypothesis 3: The backup technologies cannot recover their costs solely by the EoM. The level of cost recovery strongly depends on the weather and the availability of battery storage

Hypothesis 4: A well-designed regulatory intervention which rewards the contribution to the security of supply can reduce costs for the consumer and improves the supply ratio.

The first three hypotheses are directly addressed by the simulation results. The linked simulation process is in the experiment design. The data basis for the two experiments and its scenarios is described in scenario specification. Before the fourth hypothesis is analyzed based on the simulated missing money of the backup technologies, the experiments results are tested in a sensitivity analysis, whose structure is described in the following as well.

6.1 Experiment Design

The investigation requires a two-step procedure. First, the scarcity incidents which the backup technology needs to address are identified in a set of simulations without backup capacity. Therefore, a set of scarcity indicators are established. In the second step, a backup technology which is dimensioned to address the scarcity incidents of the worst case is implemented. The income of the backup technology is derived in a set of simulations.

The set of simulations is based on the selected scenarios (see figure 28). The changing parameters for the scenarios are determined according to the first and second hypothesis. The scenarios are built on extreme cases which demonstrate the range of impact which the parameters can have on the indicators.

In the reference scenario, the worst weather conditions with little renewable output are merged with a moderate level of installed storage capacity. In the scenario mild weather, the deviations of the scarcity indicators and the cost recovery are tested for a mild weather year with more renewable output. In the scenario no storage, the impact of the storage on the scarcity and cost recovery is emphasized.

Scenarios for Experiments	Weather Year	Storage
Reference	Extreme	Basic Storage
Mild Weather	Mild	Basic Storage
No Storage	Extreme	No Storage

Figure 28: Scenarios for the experiments

The described procedure results in two experiments using the same set of three scenarios. The outcome of the experiments is highly depended on the input parameters. This is demonstrated by the sensitivity analysis. Therefore, the generalizable insights of the experiments are not based on the total values but the changes of the indicators for the different scenarios.

6.2 Sensitivity Analysis Design

The design of the input parameters is carefully considered and based on a literature research. Nevertheless, the depicted future vision of the energy market is built on forecasts, which impose uncertainties. It is important to understand how a change of the parameters would impact the final outcome and how robust it is.

The sensitivities which are examined focus on the installed capacity of the storage, the amount of information about the future dispatch for the storage, the level of missing investment and the share of renewables (see figure 29). The same set of indicators is used for the sensitivity analysis like for the experiments to demonstrate the deviation.

Scenarios for Sensitivities	Capacity of the Storage	Foresight of the Storage	Investment Restraint	Renewable Share
Reference	Basic Storage	One Day	Basic Investment Restraint	Basic Renewable Share
More Storage	2 x Reference	One Day	Basic Investment Restraint	Basic Renewable Share
1 Week Foresight	Basic Storage	7 x Reference	Basic Investment Restraint	Basic Renewable Share
1 Month Foresight	Basic Storage	30 x Reference	Basic Investment Restraint	Basic Renewable Share
Less Investment Restraints	Basic Storage	One Day	50% Reference	Basic Renewable Share
Higher Renewable Share	Basic Storage	One Day	Basic Investment Restraint	125% Reference

Figure 29: Scenarios for sensitivities

6.3 Scenario Specification

Before the Dunkelflaute and the missing money of the backup technologies can be simulated, the electricity system on which the simulation is based needs to be designed. The following questions need to be considered:

Supply and Demand: How does the generation mix look like in a renewable dominated system? Which technologies are the remaining conventional power plants? How is the demand is going to develop?

Flexibility: How much flexibility is already in the system without any additional incentives? To which extent is this flexibility limited?

Weather: Which weather years represent the extreme cases? How great are the differences between the weather years? Are weather years repetitive? If yes, in which timely dimension do they repeat usually?

The underlying input data is derived from recent literature. As some parameters correlate, the data basis shall be as consistent as possible. For example, a higher level of demand needs to be matched with more installed capacity. Otherwise, scarcity is provoked inadvertently.

The focus of the thesis is set on a renewable dominated system. The data should reflect on the renewable targets by the German government and be at the same time compatible with the data standards and structures of AMIRIS. EnDAT provides the time series for the renewable generation dependent on the weather years and for the demand. A renewable mix which is matching with these time series is provided by (Cebulla, 2017). In his dissertation, an optimized scenario for the storage implementation in a renewable dominated electricity system is created with the optimization model ReMix. For a consistent data set, the entire generation mix and the yearly demand by (Cebulla, 2017) are used. Compared to nowadays, the demand is decreasing to 513 TWh per year. To be in line with the decarbonization goals of the German government, the scenario with a high CO_2 price of 75 EUR/t is used. 95 percent of the installed capacity by conventional power plants are gas power plants.

38 GW of different storage technologies is installed in the scenario with high CO_2 prices by (Cebulla, 2017). ReMix gives a costs-optimal mix to cover the demand. Possible investment restraints due to uncertain business cases are not considered. The research question of the thesis presupposes lacking investments, as the volatile market conditions send no sufficient investment signals. Therefore, the storage technologies with an uncertain business case (e.g. power-to-hydrogen) are neglected and only the 15 GW lithium-ion storages are used[14].

The impact of more installed storage capacity is tested by the sensitivity analysis. On the one hand, the impact of the double installed capacity of short-term flexibility is examined. On the other hand, the impact of more long-term flexibility is examined. As only one storage can be implemented in AMIRIS, more gas turbines are installed in this case instead of long-term storage.

Apart from the installed capacity, the storage can be described by three variables in the model. On the one hand, it is determined at which time the storage can discharge its energy by the energy-to-power ratio. A typical value for battery storage of 5 is used (Zapf, 2017). On the other hand, the foresight and planning horizon indicate to which extent the storage knows the future dispatch and how far in advance it schedules its bidding. A limited foresight and planning horizon of one day is used. To test the impact of a longer foresight, one week and one month are simulated in the sensitivity analysis.

The input data shall not only be compatible with the model AMIRIS but represent a power system which is dominated by renewables similar to the German renewable targets for 2040 or 2050. The generation mix by (Cebulla, 2017) results in a renewable share of 61 percent of the overall consumption for the weather year 2010. This is lower than the German renewable target for 2040 of 65 percent (BMWi, 2016). Only for 12 percent of the hours over the year, the renewables determine the price.

For a higher share of renewables in the generation mix, the installed onshore capacity from the long-term forecast by the Federal Ministry of Economics, Technology, and Energy (BMWi) is used (Pfluger et al., 2017). The additional 20 GW onshore capacity creates a renewable share similar to the 2040 goal (66 percent for the weather year 2010). For 17 percent of the hours over the year, the renewables determine the price. The generation mix of both sources and the resulting one for the simulation is depicted in figure 30.

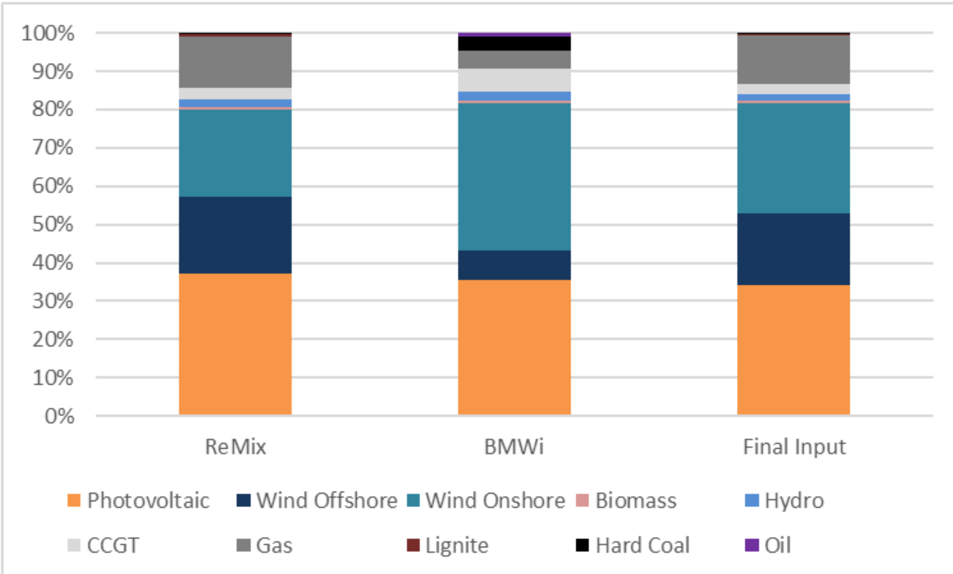

Figure 30: Generation mix for simulation

In 2050, at least 80 percent of the consumption shall be covered by renewables (BMWi, 2015). Therefore, the impact of an even higher share of renewables is tested in the sensitivity analysis. (Ram & Bogdanov, Dmitrii; Aghahosseini, Arman; Breyer, 2017) highlight photovoltaic and especially decentralized photovoltaic and battery storage combinations as the main enabler for power systems which are fully based on renewables. By adding 50 GW photovoltaic, a similar level as the target for 2050 is reached (77 percent for the weather year 2007)[15].

In the simulation, the renewable receive the current level of market premium. Even though this does not represent the subsidy conditions of the future electricity system, it ensures that the excess energy by the renewables is traded in the market and not directly curtailed.

To understand the impact of the weather on the security of supply and cost recovery of backup technologies, a realistic constellation of different weather years needs to be created. Solid assumptions would require a long-term analysis of interannual meteorological patterns. As an in-deep research like this is not possible due to time constraints, two contrary extreme cases are analyzed to give the range of possible outcomes. Hence, an extreme weather year with a low renewable output and a mild weather year with a high renewable output are used for the analysis.

For the selection of the weather years, the generation pattern of the renewables based on weathers years from 2006 to 2012 by ReMix are used. The attributes of one weather year impose different challenges for the system. For instance, figure 31 shows the residual load of one day for different weather years. The weather year 2006 and 2010 have the same amount of residual load in this period, but a different temporal distribution. 2006 is characterized by the two extreme peaks of the residual load. In contrast to that, 2010 has a longer duration of consecutive hours with the high residual load. Whereas the situation

[15] The installed capacity for other generators remains the same like in the reference scenario. Only the impact on the scarcity and the income of the backup technologies shall be tested.

in 2006 requires a backup technology which is capable of ramping up and down for these single peaks, the situation in 2010 asks for a backup technology which can supply energy over a longer period.

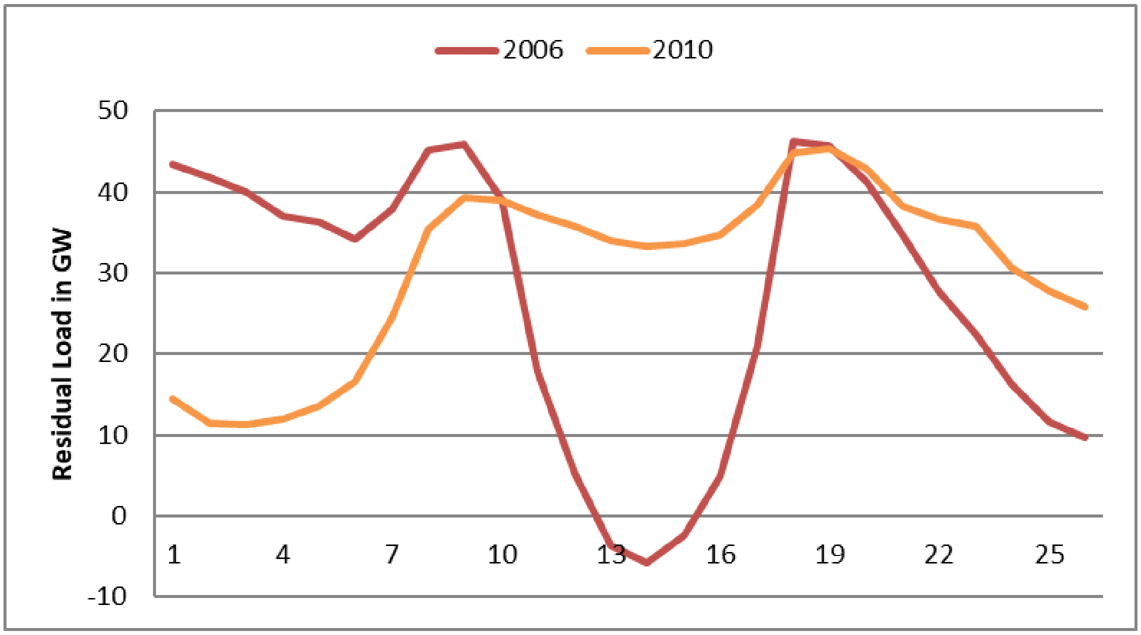

Figure 31: Selected hours of the residual load for the weather year 2006 and 2010

Hence, three indicators for ranking weather years as a challenge for the electricity supply are given. First of all, if the average wind yield and photovoltaic radiation are low during the entire period, it is a challenge of the total uncovered load. It is measured by the amount of uncovered load per period (GWh). If the uncovered load is rather equally spread over the entire period with some hours of sufficient supply in between, battery storage can bridge the scarcity. Secondly, if the wind radically stops to blow and the sun stops to shine at the same moment during a high demand, it is a challenge of the maximum uncovered load peak. The capacity at this extreme moment is measured in GW. The production of the industry can pause for a short while to bridge this kind of scarcity. Finally, if the wind and solar radiation are short during some hours, it is a challenge of the duration of consecutive uncovered load. It is measured in the uncovered load during these intervals. Gas turbine could bridge a longer period of scarcity like this.

The most extreme and mild weather years are selected based on the match of the three scarcity indicators.

Looking at the demand, which still needs to be covered by other sources than the renewables, the weather years 2010 shows the biggest amount of residual load per year. The weather years 2007 shows the least residual load (see figure 32).

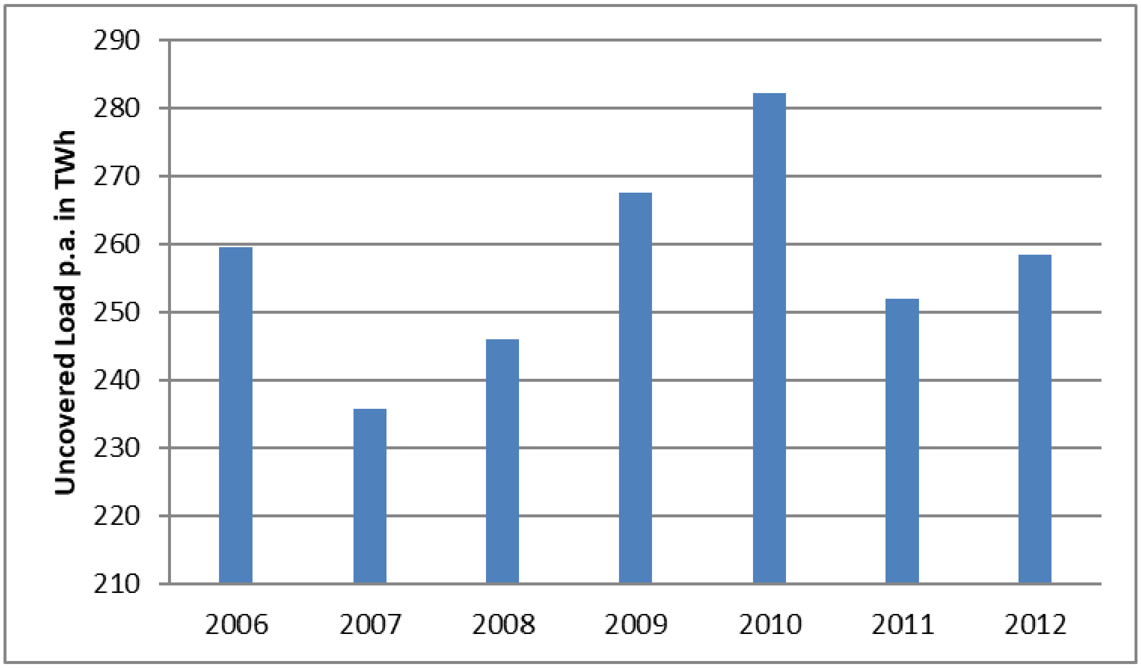

Figure 32: Residual load per year for the weather years 2006 to 2012

The highest load peak with almost 83 GW is shown by the weather year 2010. With the high consumption of 90 GW and the lowest renewable production of 7 GW, this hour merges two extreme values of demand and supply (see figure 33).

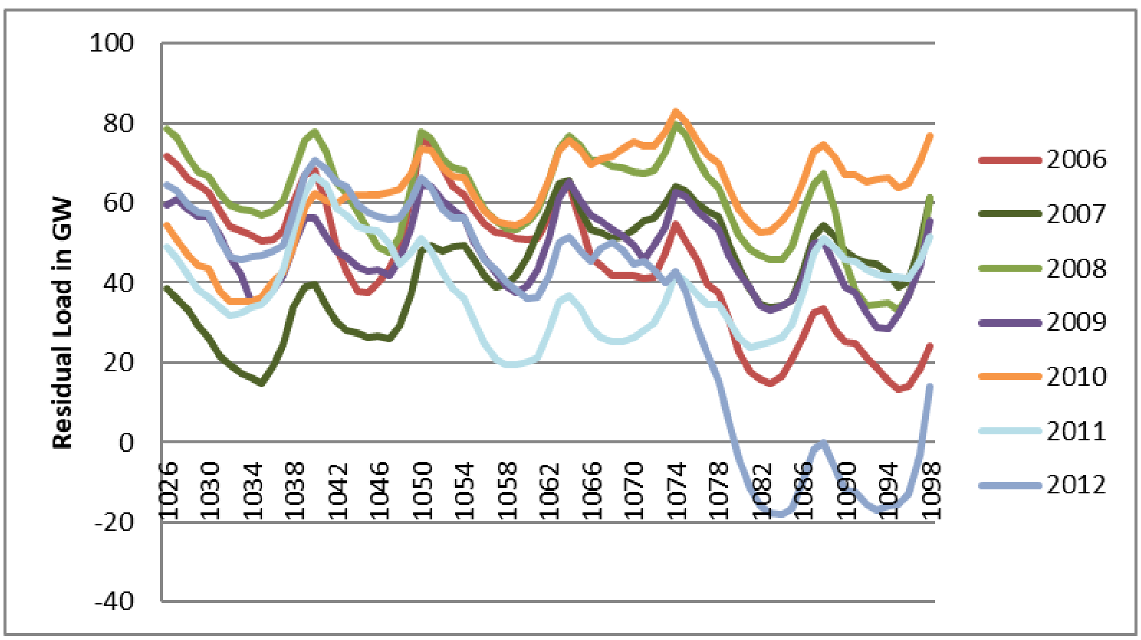

Figure 33: Period with the maximum uncovered load for all weather years

Even with a high share of renewables, other generation sources are still available and can cover the load to some extent. Therefore, not only hours with zero or negative residual load are considered as covered load in this preanalysis. Assuming that other generation sources cover a certain level of residual load, the value between the highest and lowest residual load is used as a threshold for scarcity. Hours with a residual load above 55 GW are considered as scarcity moments. The longest period with a continuous residual load above 55 GW can be found for the weather year 2010 with 65 hours (figure 34). The sum of the residual load is 4 313 MWh. In contrast to that, the longest scarcity period in 2010 has more than three times more residual load than the one in 2012. In figure 35, these periods are depicted. The amount of periods above 55 GW (regardless of its duration) ranges between 152 periods in 2008 and 202 periods in 2010.

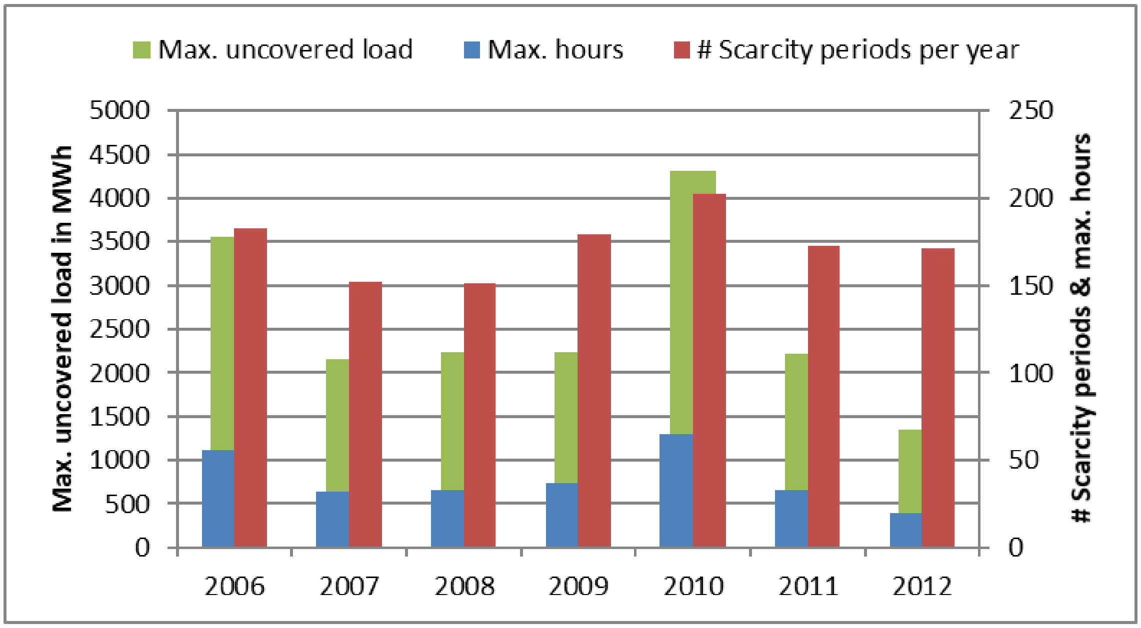

Figure 34: Overview of the indicators for scarcity periods for the weather year 2006-2012 based on residual load

Like summarized in figure 35 and 36, the weather year 2010 shows the largest amount of residual load per year, the longest duration of consecutive positive residual load and the maximum peak of the residual load and is selected as extreme weather year. The level of consecutive residual load is similar for the weather year 2007 and 2008. As 2007 has the least residual load per year as well, it is used as mild weather year.

		2006	2007	2008	2009	2010	2011	2012
Residual Load (RL) p.a.	[TWh]	260	236	246	268	282	252	258
Max. RL	[GW]	77	81	80	79	83	80	83
Max. consecutive RL	[GWh]	3.55	2.15	2.23	2.24	4.31	2.22	1.35
Amount RL Periods	#	183	152	151	179	202	173	171

Figure 35: Overview of scarcity indicators for the different weather years (table)

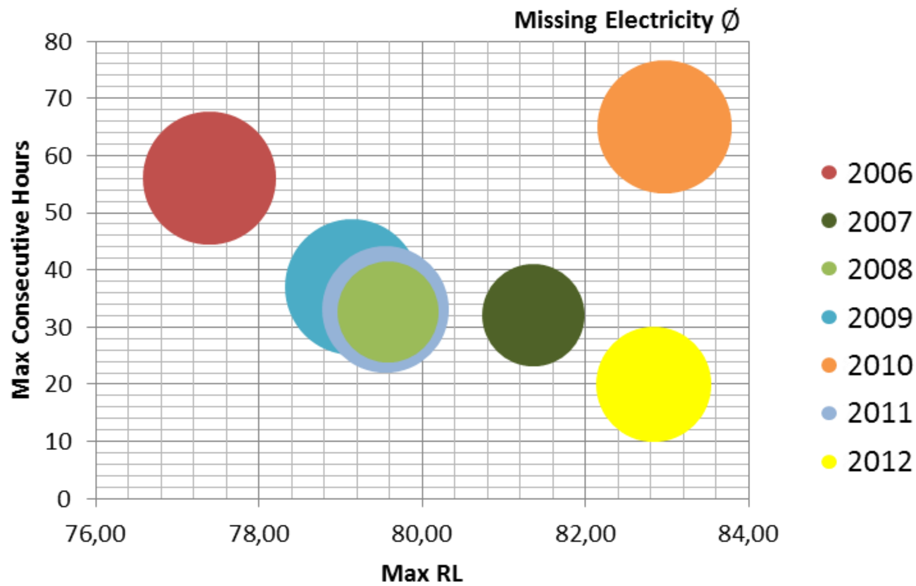

Figure 36: Overview of scarcity indicators for the different weather years (graph)

7 Experiment 1: The Severity of Scarcity depending on Weather and Battery Storage

The goal of the first experiment is to describe the scarcity incidents depending on weather conditions and the availability of battery storage. Thereby, the impact of these two parameters on the scarcity is demonstrated and the requirements for the backup technology is defined. The indicators refer to the entire weather year. To illustrate the severity of scarcity, the zoom on the Dunkelflaute of every year presented as well.

The basis for the comparison, the reference scenario, is presented with the first alternative scenario mild weather. Afterwards, the analysis of short-term flexibility follows.

7.1 Weather Year Analysis

The share of provided energy by renewables on the total consumption is 72 percent in 2007 and 66 percent in 2010. Whereas photovoltaic has a similar daily and seasonal output in both weather years, the output by wind onshore is ca. 25 percent less for the weather year 2010. The way how the onshore output in 2007 contributes more to the covering of the load than in 2010 is depicted by the example of the month January in figure 37 below.

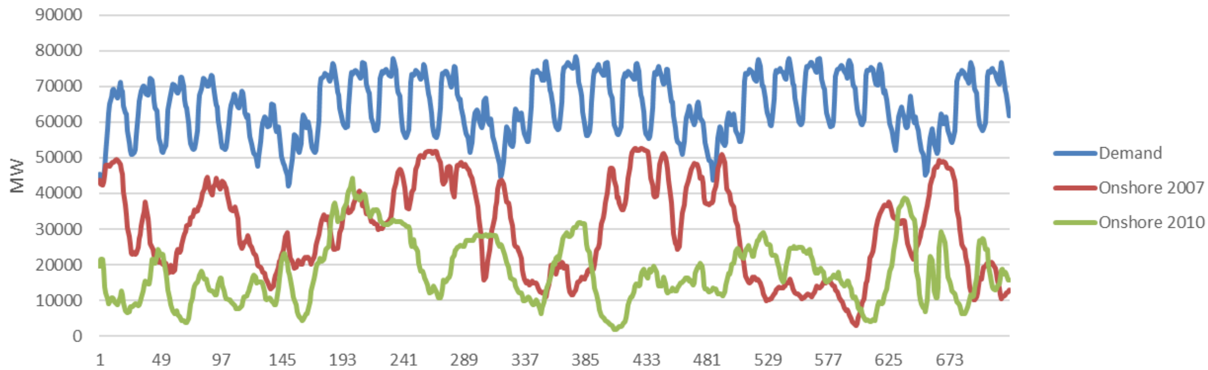

Figure 37: Comparison of wind onshore output for the weather year 2007 and 2010

The total amount of the provided energy and their match with the demand in every hour of the year lead to a different level of uncovered load for 2007 and 2010. With 2 TWh (2007) and 2.5 TWh (2010), the sum of uncovered load per year is 25 percent higher for 2010.

Whereas the amount of uncovered load per year differs, the maximum uncovered peak of ca. 26 GW is similar (see figure 38). This is ca. one-third of the demand in that moment and one-quarter of the higesht demand per year. For 2007, this moment occurs by the end of the year and for 2010 in the middle of February. In both hours, a low level of renewables meets a high level of demand (83 percent of the maximum demand). In both cases, the total amount of conventional energy is used, but no storage[16].

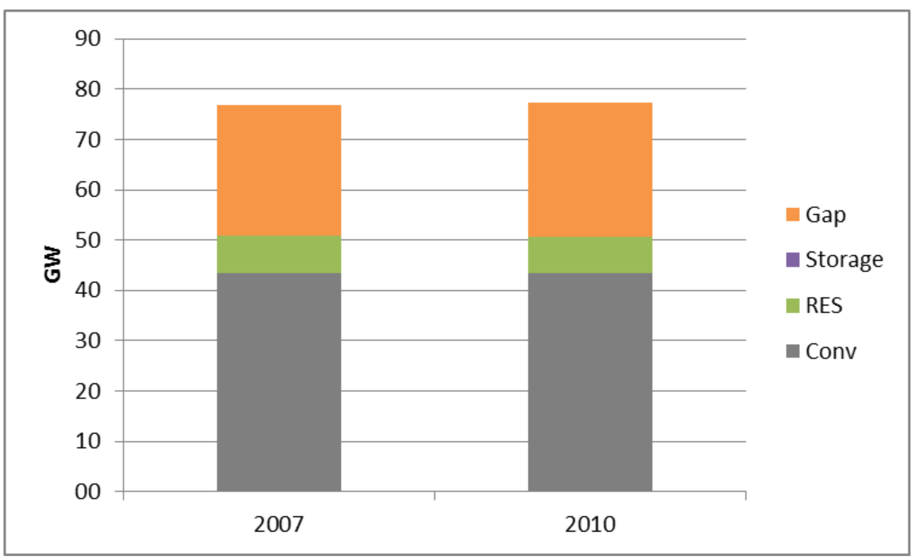

Figure 38: Maximum uncovered load peak for the weather year 2007 and 2010

The histogram about different levels of peaks for both weather years shows a decreasing tendency in the amount with an increasing level of peaks (see figure 39 and 40). The graph gives an idea to which extent limited flexibility potentials could contribute to maintain the security of supply. For example, in the given

[16] The usage of storage is explained in the storage analysis part

scenarios, the industrial demand shedding with maximum 6.3 GW half of the peaks for both year by themselves, when the hours with a peak of 1 GW and 2 GW are considered as well (Geipel, 2016)[17].

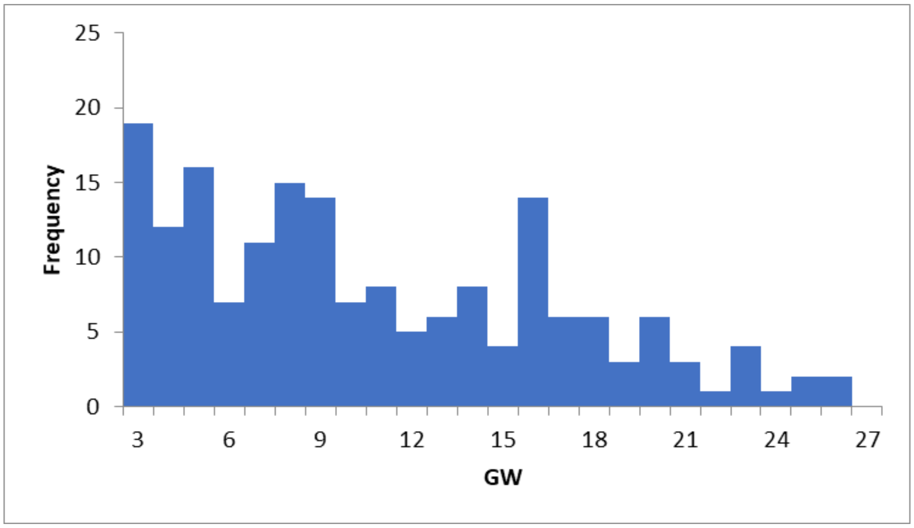

Figure 39: Distribution of uncovered load peaks in context of its frequency for the weather year 2007

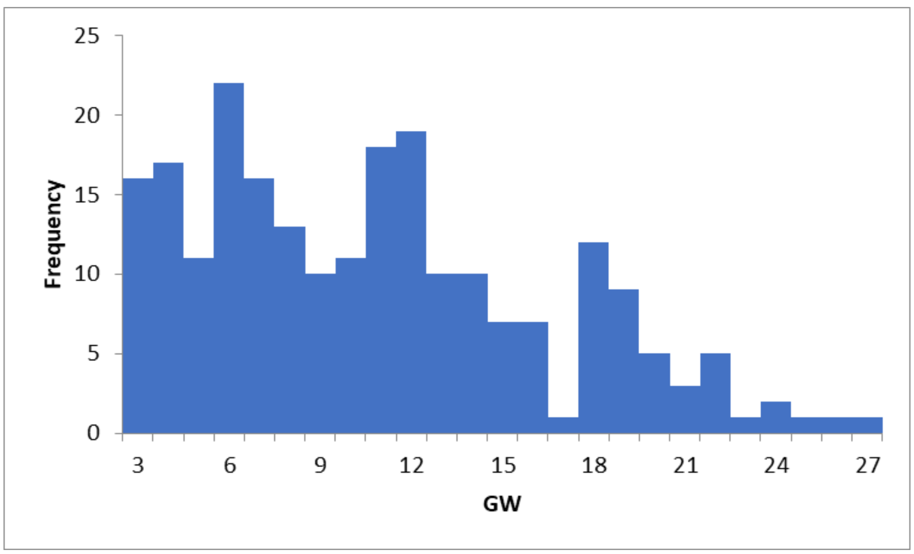

Figure 40: Distribution of uncovered load peaks in context of its frequency for the weather year 2010

Looking at the differences in the frequency (see figure 41), the weather year 2010 shows more peaks in general. Especially in the mid-range of 10 to 20 GW, 36 percent more peaks are shown than for 2007.

[17] If no more than four hours of these peaks are consecutive

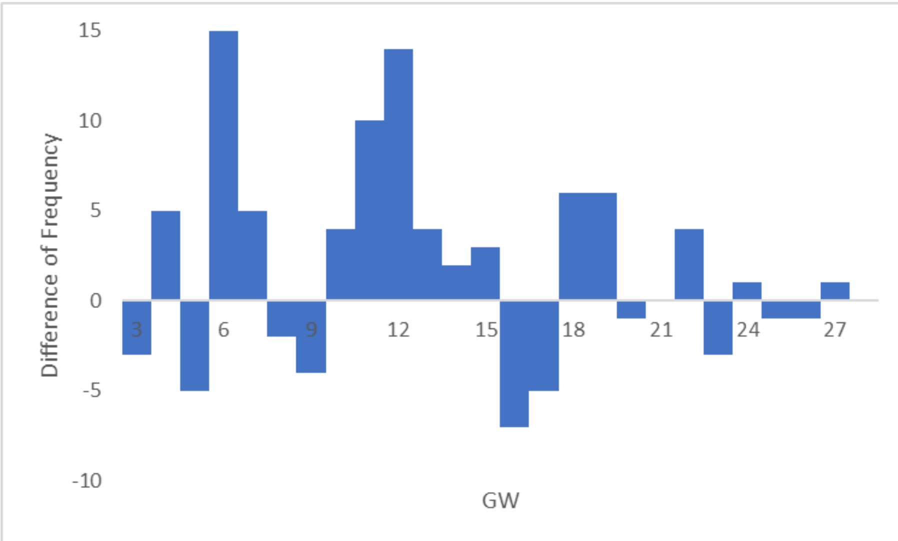

Figure 41: Difference of the distribution of uncovered load peaks in context of its frequency for the weather year 2007 and 2010

Remark: Negative value: higher value for 2007 - positive value: higher value for 2010

Looking at the continuity of the scarcity, the longest period with consecutive hours without covered load is in 2010 three times higher than in 2007. Also, the uncovered load during these two extreme periods is almost three times higher for 2010 than for 2007. Regardless of the duration of every scarcity period, its amount is 20 percent higher in 2010 than in 2007.

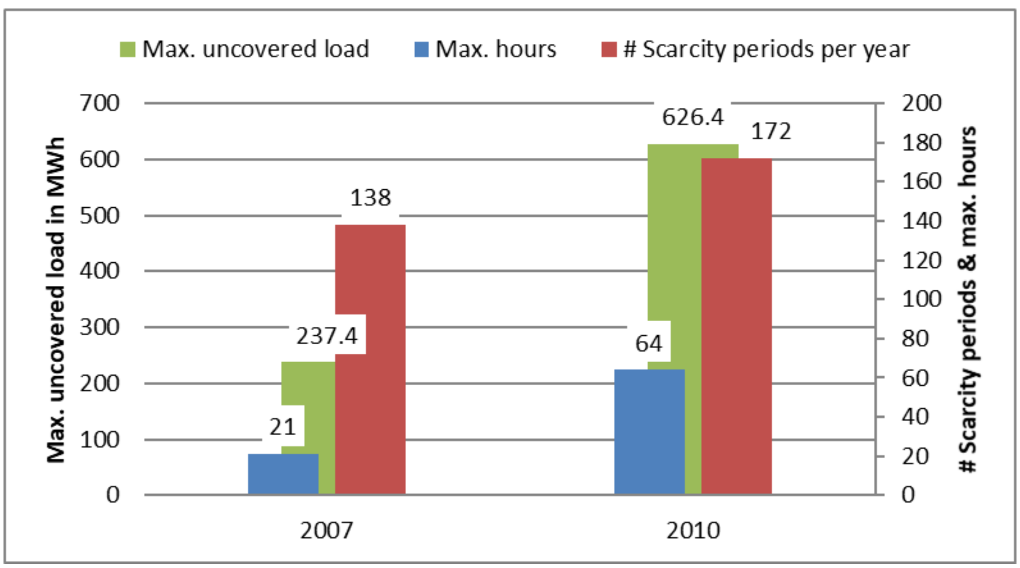

Figure 42: Overview of indicators for scarcity periods for the weather year 2007 and 2010

Bridging the scarcity becomes especially a challenge when high scarcity peaks are surrounded by further hours by the uncovered load. The graph below shows the timely correlation between peaks larger than 10 GW, 15 GW or 20 GW and periods with consecutive hours of uncovered load longer than 5 hours, 10 hours, 15 hours or even 20 hours (see figure 43 and 44).

Generally speaking, the weather year 2007 shows a lower number of peaks for every category than 2010. The bridging of the peaks higher than 20 GW is difficult for both weather years. Almost all extreme peaks are surrounded by at least 5 hours of uncovered load. Single short-term flexibility providers (e.g. demand shedding by the industry) can only address some of these hours. 35 percent (2010) and 25 percent (2007) of the extreme peaks can be found in a scarcity period longer than 20 hours. Even a large amount of well-coordinated and spread short-term flexibility providers cannot address this scarcity period. Long-term backup technologies are needed.

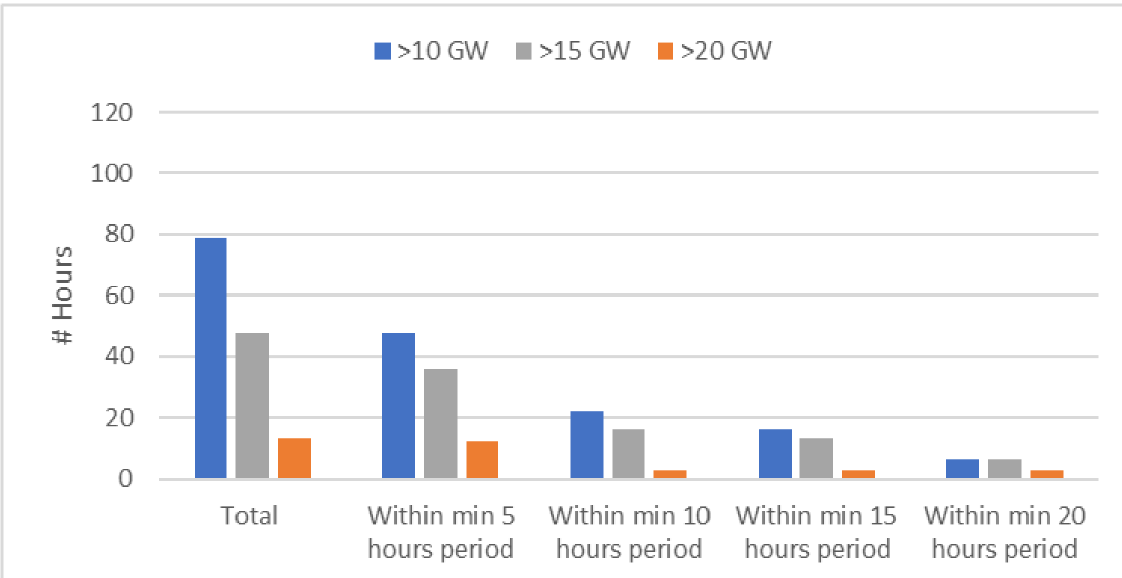

Figure 43: Correlation of hours with uncovered load peaks and consecutive hours of the uncovered load for 2007

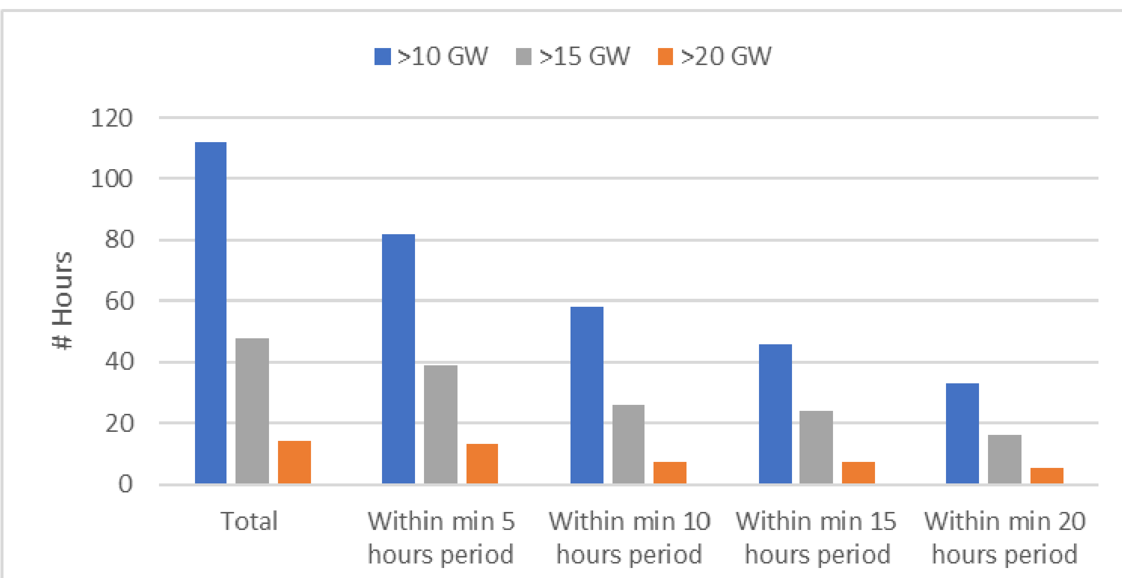

Figure 44: Correlation hours with uncovered load peaks and consecutive hours of the uncovered load for 2010

If the longest scarcity period is compared, the uncovered load is 2.6 times higher for 2010 than for 2007. The literature characterizes the Dunkelflaute as a two or three-week period with a low supply of renewables by most sources (Fraunhofer IEE, 2018; Huneke et al., 2017). Therefore, not only the longest scarcity period is highlighted, but also set in the context of the surrounding two weeks with a high uncovered load. These extreme weeks for both years also include the uncovered maximum peak and the longest period with consecutive hours without covered load.

The uncovered load curves of these two weeks are characterized by a decrease in the scarcity during the weekend (see figure 45 and 46). Whereas the uncovered load is spread in several peaks during the working days for 2007, 2010 shows two main consecutive peak periods with short breaks in between.

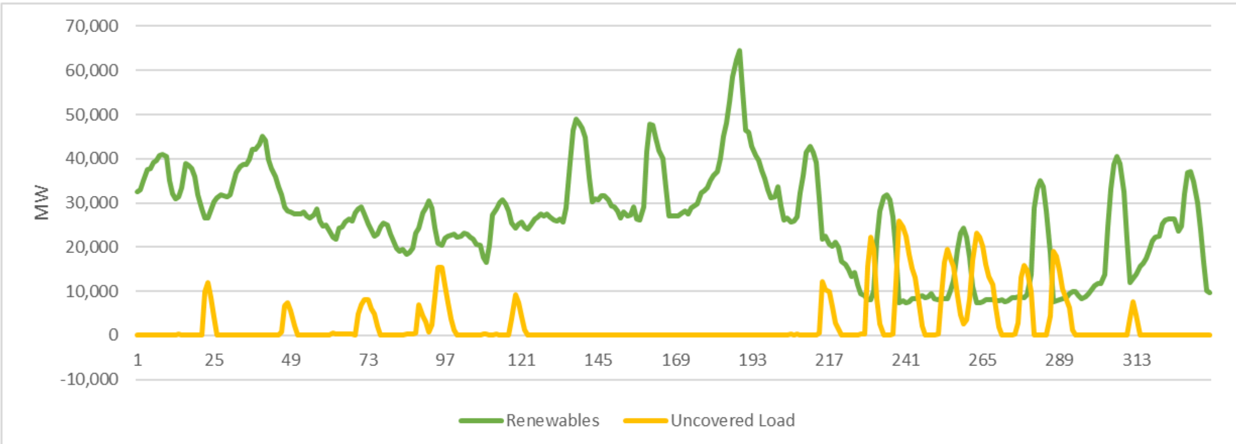

Figure 45: Dunkelflaute for weather year 2007: Renewable output and uncovered load

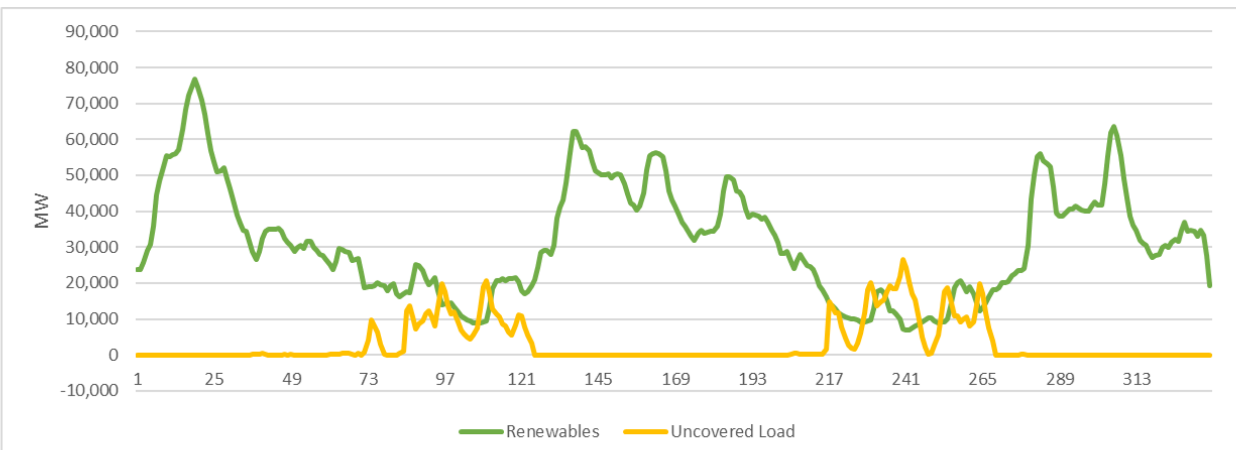

Figure 46: Dunkelflaute for weather year 2010: Renewable output and uncovered load

The uncovered load curve shows the two similar maximum peaks of 26.5 GW (2010) and 25.8 GW (2007). The number of hours of the uncovered load is slightly higher for 2010 (120 hours) compared to 2007 (113 hours).

Figure 47 shows the consecutive hours and uncovered load during the Dunkelflaute. Whereas 2007 shows more frequent but shorter periods of scarcity, the scarcity is concentrated in fewer but longer periods for 2010.

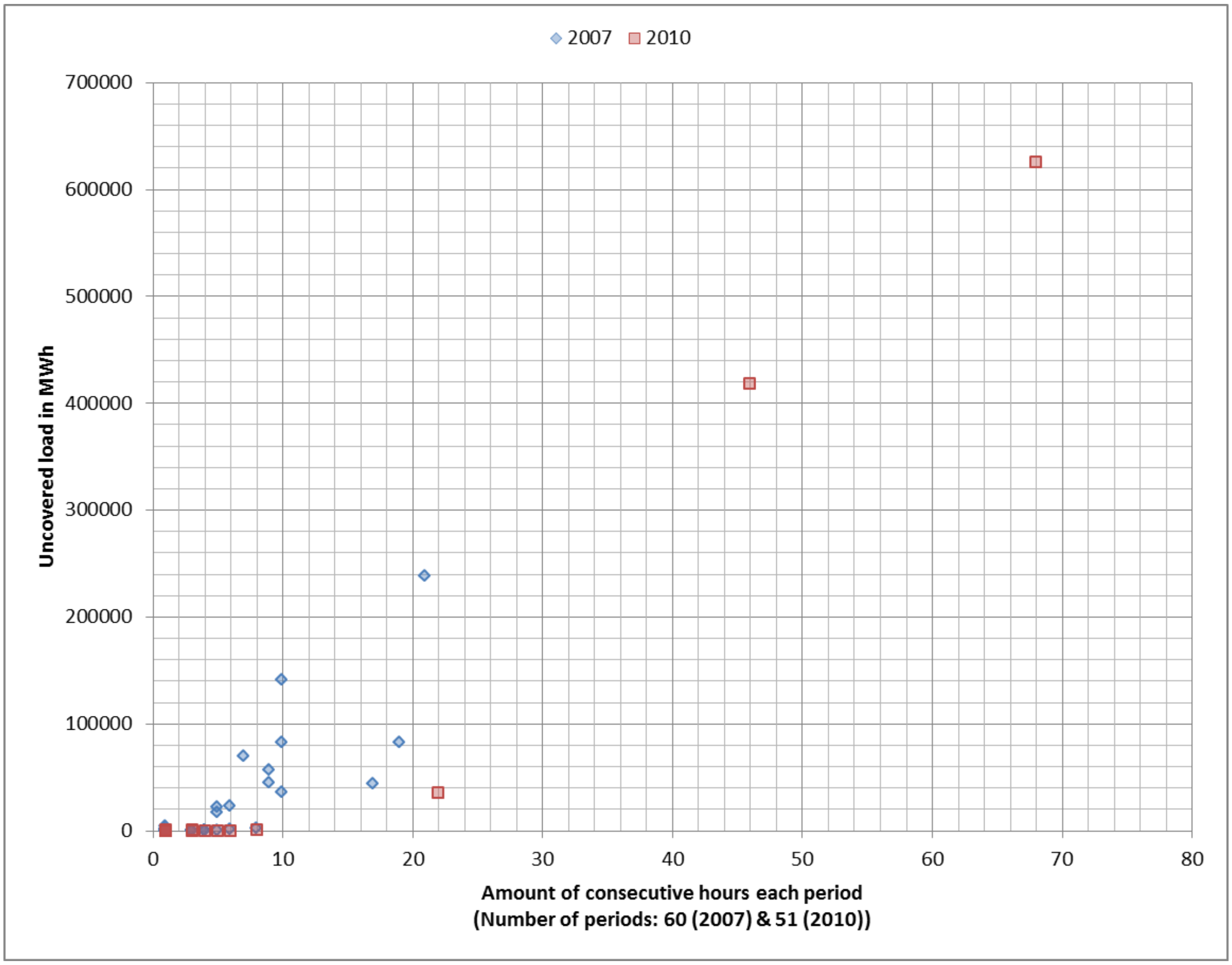

Figure 47: Dunkelflaute for weather year 2007 and 2010: Correlation of uncovered load and duration of scarcity periods

With 2.6 more uncovered load in the longest scarcity period, the weather conditions like in 2010 stand out as a stress test for a renewable dominated power system.

7.2 Battery Storage Analysis

By analyzing a scenario without battery storage, the impact of the installed 15 GW in the reference scenario is emphasized. The implemented storage divides the uncovered load per year in a half (see figure 48). As demonstrated in the weather analysis, the battery storage does not contribute to the maximum load peak. Consequently, it is 26.5 GW for the reference and no storage scenario.

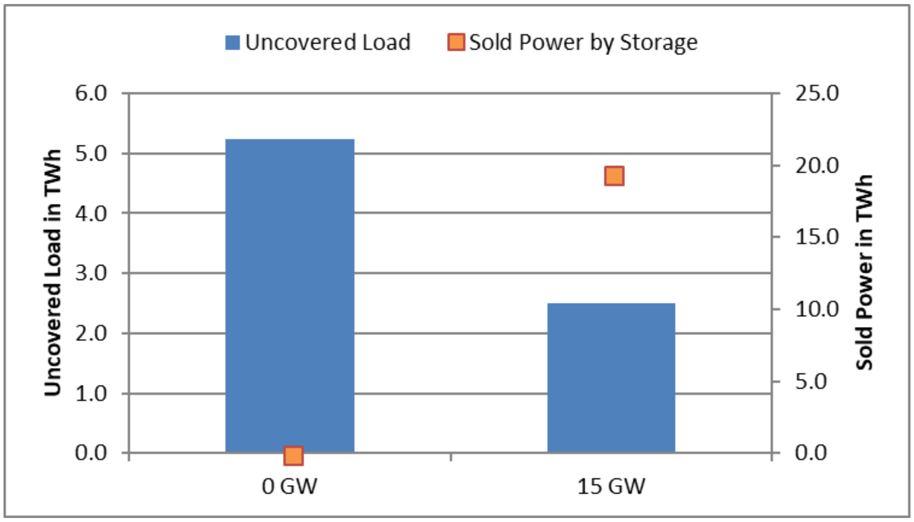

Figure 48: Uncovered load per year for 0 GW and 15 GW battery storage

In general, more energy is sold by storages than the uncovered load reduced. The storage does not only mitigate the scarcity but also replace more expensive suppliers. For instance, the number of full load hours of gas turbines is decreasing by 4.6 percent with the implementation of 15 GW storage.

The uncovered load during the longest scarcity period is lowered by 13 percent with the 15 GW storage. Nevertheless, the additional provided energy by the storage is not sufficient to reduce the duration of the longest scarcity period. Looking at the entire year, the amount of scarcity periods is slightly reduced by three percent (see figure 49).

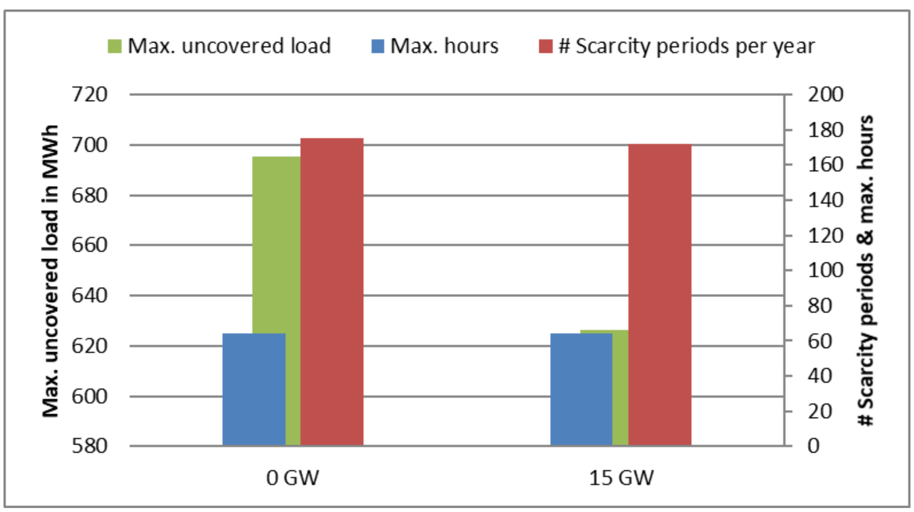

Figure 49: Overview of indicators for scarcity periods for 0 GW and 15 GW battery storage

Comparing the uncovered load during the Dunkelflaute with and without storage, the storage contributes to a 15 percent reduction. In one hour, the storage manages to divide the uncovered load by six. The duration of the discharging periods ranges from two to 14 hours (see figure 50).

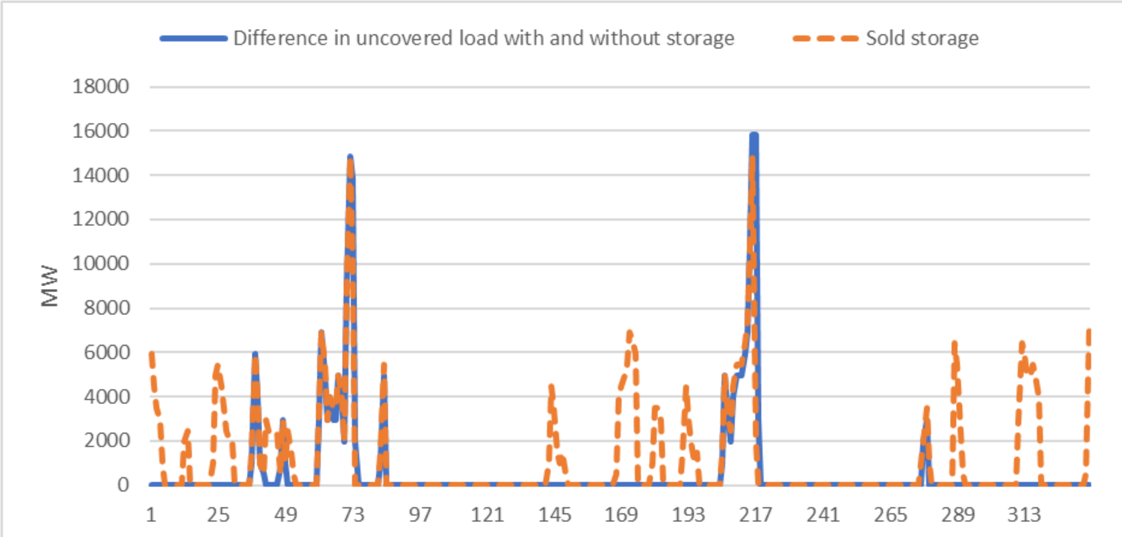

Figure 50: Dunkelflaute and contribution of battery storage for reference scenario

7.3 Conclusion

The impact of the weather conditions and the level of short-term flexibility on the security of supply are demonstrated by the first experiment. Along the three indicators, a different severity of scarcity is shown (see figure 51).

The maximum uncovered load peak remains on a similar level for all scenarios. It implies that the combination of supply and demand can always lead to one hour in which the demand is high, the residual load low and the storage not available regardless of the weather year and the level of battery storage.

In contrast, the weather conditions and level of battery storage influence the amount of missing energy. The 15 GW battery storage is able to divide the yearly missing energy in a half. One fifth less missing energy per year needs to be covered in the case of the mild weather year compared to the extreme one.

The severity of the scarcity become more explicit for the investigation of the longest scarcity period of each year. The missing energy is ca. three times higher for the extreme weather year than for the mild one. The condensed accumulation of scarcity moments can be pinpointed as Dunkelflaute. It cannot be addressed by the battery storage. Due to the limited eligible moments to charge, the contribution of the battery to cover the missing energy is ca. one-tenth less than for the observation of the entire year.

In conclusion, the observation of the extreme scarcity moments within one year makes explicit that those cannot be covered solely with short-term flexibility. The maximum peak asks for the similar level of installed backup capacity for all scenarios but under a greatly changing request for energy for the rest of the year depending on the weather conditions and availability of battery storage.

	Scenarios	Experiment 1			Experiment 2	
		Uncovered load per year [TWh]	Maximum uncovered load [GW]	Max. consecutive uncovered load [MWh]	Average price with backup capacity [EUR/MWh]	Margin for backup technology [Mio. EUR]
Experiment	**Reference**	**2.5**	**26.5**	**626.4**	***	***
	Mild Weather	-20.0%	-2.3%	-62.1%	***	***
	No Storage	+108.0%	0%	+11.0%	***	***
Sensitivity	2 x Storage	***	***	***	***	***
	1 Week Foresight	***	***	***	***	***
	1 Month Foresight	***	***	***	***	***
	50% less Investment Restraints	***	***	***	***	***
	Renewable Share like 2050	***	***	***	***	***

Figure 51: Summary of experiment 1 -– percentages express the difference compared to the reference scenario

8 Experiment 2: The Impact of Weather and Battery Storage on the Cost recovery of Backup Technologies

To bridge the scarcity, a backup technology is implemented in this experiment. The aim of this simulation is to determine the income of the backup technology, match it with its total costs and calculate the margin. By using the same scenario set like in the first experiment, the impact of a change of the weather year or level of short-term flexibility on the cost recovery is demonstrated.

As the scarcity is covered by the additional installed capacity no extreme prices occur in these simulations. Therefore, the highest price is set by the bid of the peaker, the gas turbine, or the storages, if they see the chance to optimize their bid.

The technology analysis recommends application with fossil gas for a relatively low yearly amount like 2.5 TWh. As gas turbines can respond faster to scarcity incidents than CCGT, additional capacity is added to the before already installed 7 GW gas turbines. Considering the maximum scarcity peak of the reference case, the non-availability rate, and an additional 10 percent security margin, 30 GW are installed as backup capacity. A proper distinction between the specially installed backup capacity and the already existing capacity is not possible. Therefore, the cost recovery of the entire 37 GW gas turbines is analyzed in the following.

The same cost structure as in the technology analysis is used. The cost recovery depends on two factors, the amount of sold energy by the gas turbines and its dispatch price. Both multiplied give the income. To gain a profit, the yearly total costs need to be lower than the sum of the hourly income.

8.1 Weather Year Analysis

The margins for both weather years are negative. As the storage bids sometimes for a higher price than the variable costs of the gas turbine, the income is higher than the variable costs of the gas turbine. Nevertheless, this surplus is not sufficient to cover the fixed costs (see figure 52).

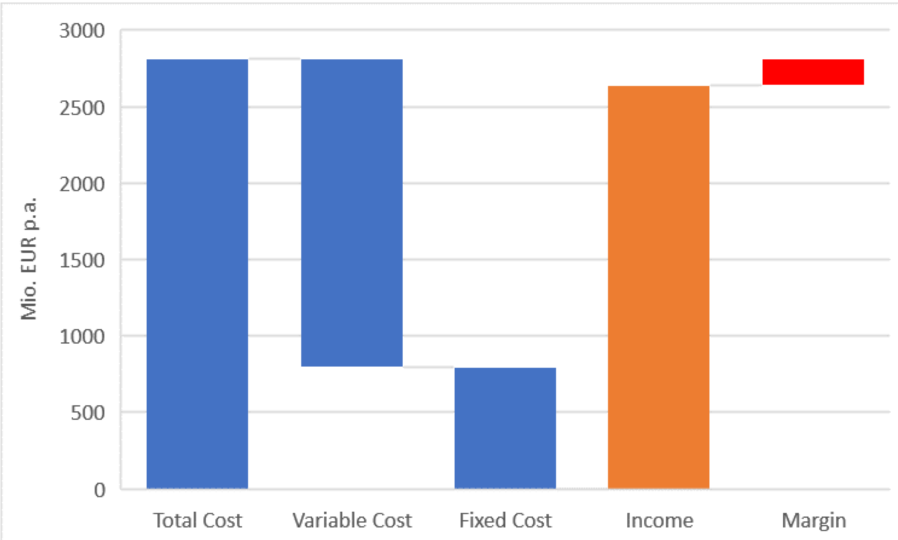

Figure 52: Cost structure and profit margin of backup technology for reference scenario

The weather year 2010 is highlighted in the previous chapter as the worst conditions for the security of supply. Those are at the same time best conditions for the cost recovery of backup technologies. In case of the mild weather year 2007, the margin is almost two times lower than for the weather year 2010.

For 2007, only 2932 hours exist with prices higher than the marginal costs of the gas turbine exist; for the year 2010, price occurs 30 percent more often.

During these hours with prices above marginal costs, the awarded energy by the gas turbines is also higher for 2010 than for 2007. Over the year, 7.3 TWh are more sold for 2010 than in 2007 (see figure 53).

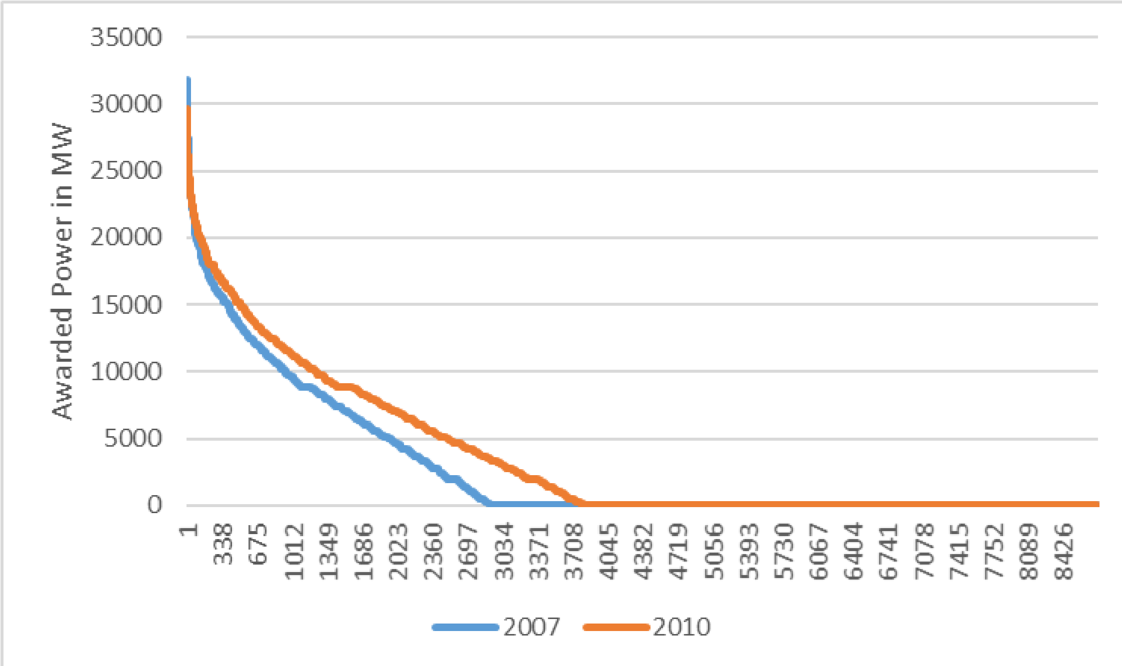

Figure 53: Awarded energy of backup technology for 15 GW battery storage and the weather year 2007/2010

Due to the fixed costs, a lower usage of the gas turbine is not reflected to the same extent in a costs reduction. With a lower amount of full load hours, it becomes more challenging to cover the same amount of fixed costs. The reduction of the yearly produced energy results in the strong decrease of the margin.

To cover the negative margin, the gas turbine would need to earn on average 24 EUR/MWh more with the same amount of awarded energy for the weather year 2007 and 6 EUR/MWh more for 2010.

8.2 Battery Storage Analysis

The battery storage replaces conventional power plants with higher bids. With the implementation of 15 GW storage, the full load hours of gas turbines decrease by 6 percent. This results in a more than four times lower margin than in the case without any storage (see figure 54).

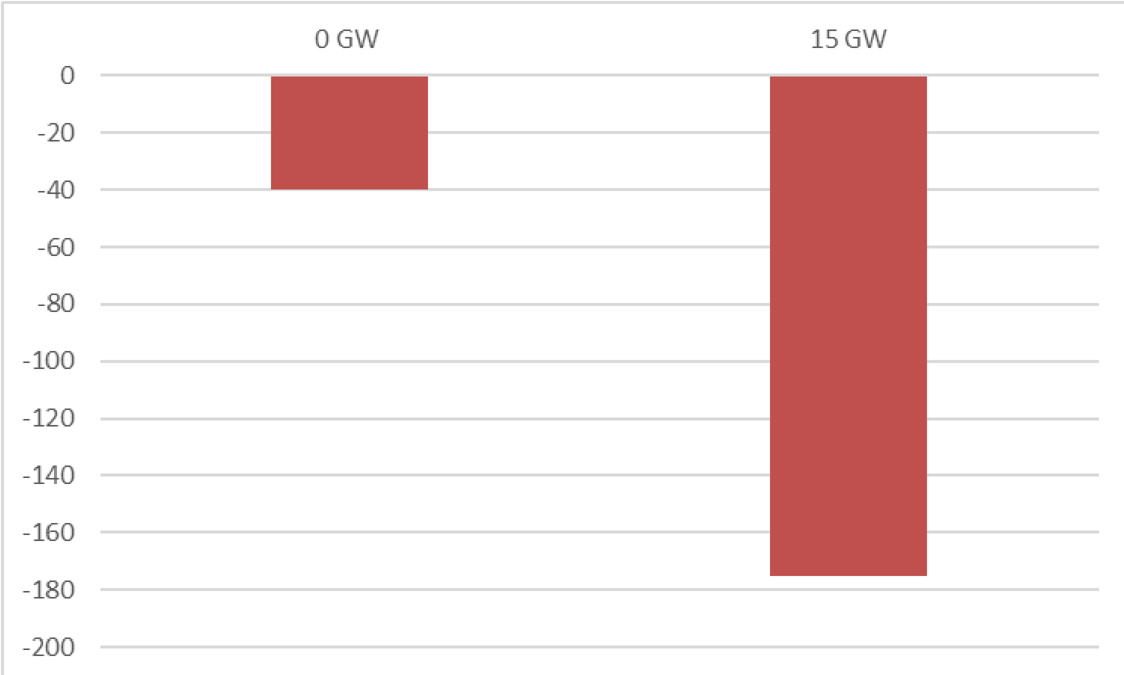

Figure 54: Profit Margins of backup technology for 0 GW and 15 GW battery storage

8.3 Transfer of the Experiment Results to Power-to-Methane

The bidding of more than one storage is complex to implement in the model. For instance, the unawareness of the bidding of the other storage party makes it difficult to align its own arbitrage bidding strategy. For the analysis of the thesis, only one storage party can be considered. Therefore, the income of a power-to-methane entity is not simulated. To compensate for this missing information, the results for the gas turbines are transferred in a simplified way to the power-to-methane.

The most serious drawback of this approach is that the charging of the storage is not simulated. The prices for charging and consequently the delta between the charging and discharging prices are unknown. This lead to two simplifications. First, the costs of charging cannot be determined. To compensate for this limitation, the acquisition of energy is assumed to be not done at the wholesale market, but via bilateral contracts with the renewables operator. More energy which is offered to negative prices than consumed by the electrolyzer exists. Therefore, the excess energy can be offered for a price which only covers the variable costs of the renewables[18].

Second, it is assumed that the power-to-methane entity and the gas turbine with fossil fuel offer the same amount in the same hours. Although it is correct that both entities strive for high prices, the amount and the timing does not need to be identical, as the costs for the fossil gas and the electricity price for the electrolysis and their technical restrictions are different.

[18] Same approach like in the technology analysis

For the dimension of the power-to-methane entity, the same installed capacity of the gas turbine is used. Instead of the fossil gas, the synthetic gas transformed from electricity to hydrogen and from hydrogen to methane is used.

The power-to-methane entity shall provide the same amount of energy as the gas turbine with fossil fuel. With an efficiency of 51 percent for the transformation from electricity to methane and an efficiency of 38 percent of the gas turbine, the power-to-methane entity needs to consume 160 TWh to provide 31 TWh in the end. 1472 hours with excess energy exist. For most of these hours (more precisely 1439 hours), more than 22 GW per hour are curtailed. By transforming steadily 22 GW into methane in the course of the 1439 hours, 31 TWh can be provided in the end. At the same time, the steady transformation allows keeping the installed capacity of the electrolyzer and methanation entity at a minimum level.

The investment costs of 900 EUR/kW, an average lifetime of 15 years and 2 percent operation and maintenance costs results in 1716 Mio. Euro installation costs p.a. for transformation from electricity to methane. The gas turbine with sufficient installed capacity to cover the peak costs 797 Mio. Euro p.a.

As the power-to-methane entity not only emits CO_2 during the electrification but also captures CO_2 during the methanation, it is considered as CO_2 neutral and does not need to pay CO_2 costs. Considering the electricity costs for the transformation to methane and the variable operation and maintenance costs, the 31 TWh results in variable costs of 193 Mio. Euro.

The total yearly costs of 2706 Mio. Euro is compared to the income of the gas turbine with fossil gas. This results in a negative margin of -70 Mio. Euro (see figure 55).

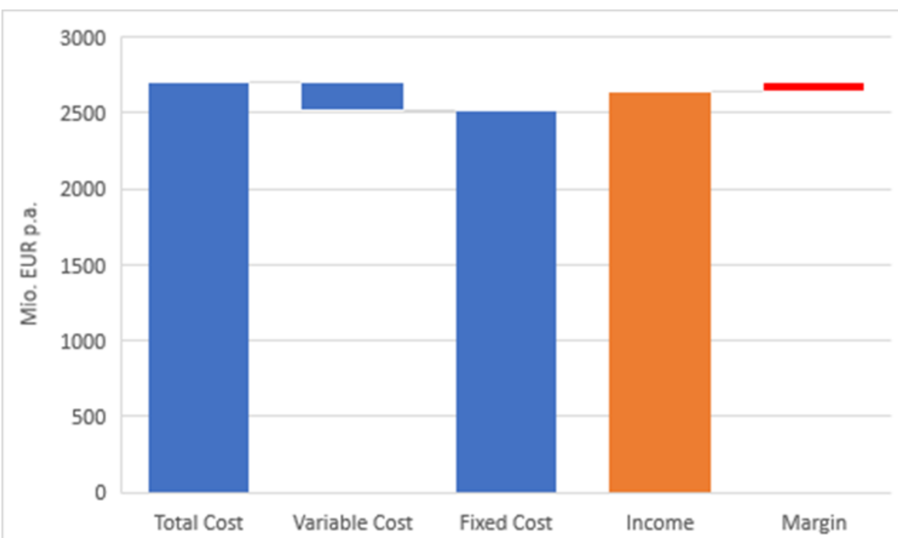

Figure 55: Cost structure and profit margin of power-to-methane[19]

In the scenario with the weather year 2007 and 15 GW installed storage, only 24 TWh are sold by the backup technology. The income decreases by 24 percent compared to the scenario used before. With the same installed capacity, the margin for 2007 is significantly lower (-576 Mio. Euro p.a.).

[19] Based on cost forecasts for 2030

8.4 Conclusion

The decrease of missing energy in the case of more storage or milder weather presented in the first experiment gives already an indication for the lower full load hours of the backup technology and its reduced margin. The mix of change of full load hours and prices of the dispatch creates the resulting margin of the second experiment for the backup technology (see figure 56).

The implementation of the storage provokes a more than three times lower margin for the backup technology. Also, the milder weather leads to a decrease of the margin by 83.5 percent. The second experiment makes explicit that the cost recovery is not only insufficient, but also a subject of great uncertainty depending on the weather conditions and available short-term flexibility.

At the same time, it needs to be considered that the backup technology does not leverage its dominant position during scarcity times to cover its cost due to the configuration of the model. A different behavior and its effect on the cost recovery is presented in chapter 10.

		Experiment 1			Experiment 2	
	Scenarios	Uncovered load per year [TWh]	Maximum uncovered load [GW]	Max. consecutive uncovered load [MWh]	Average price with backup capacity [EUR/MWh]	Margin for backup technology [Mio. EUR]
Experiment	**Reference**	**2.5**	**26.5**	**626.4**	**52.7**	**-175.2**
Experiment	Mild Weather	-20.0%	-2.3%	-62.1%	-30.6%	-83.5%
Experiment	No Storage	+108.0%	0%	+11.0%	-0.6%	+76.5%
Sensitivity	2 x Storage	***	***	***	***	***
Sensitivity	1 Week Foresight	***	***	***	***	***
Sensitivity	1 Month Foresight	***	***	***	***	***
Sensitivity	50% less Investment Restraints	***	***	***	***	***
Sensitivity	Renewable Share like 2050	***	***	***	***	***

Figure 56: Summary of experiment 2 – percentages express the difference compared to the reference scenario

9 Sensitivity Analysis

To test the robustness of the results of both experiments, a sensitivity analysis is conducted. For each part, one parameter of the reference scenario is changed. The outcome of the sensitivity analysis is measured by the same indicators as in the experiments and is compared in the end.

9.1 Duplication of Battery Storage Capacity

A duplication of the installed storage capacity from 15 GW to 30 GW contributes only slightly to the further reduction of scarcity. The uncovered load per year decreases by ca. 6 percent. For the most extensive scarcity period, the uncovered load is only reduced by 3 percent (see figure 57). Its minor impact is also linked to the stagnating full load hours at the level of 38 percent of the hours over the year for both storage levels.

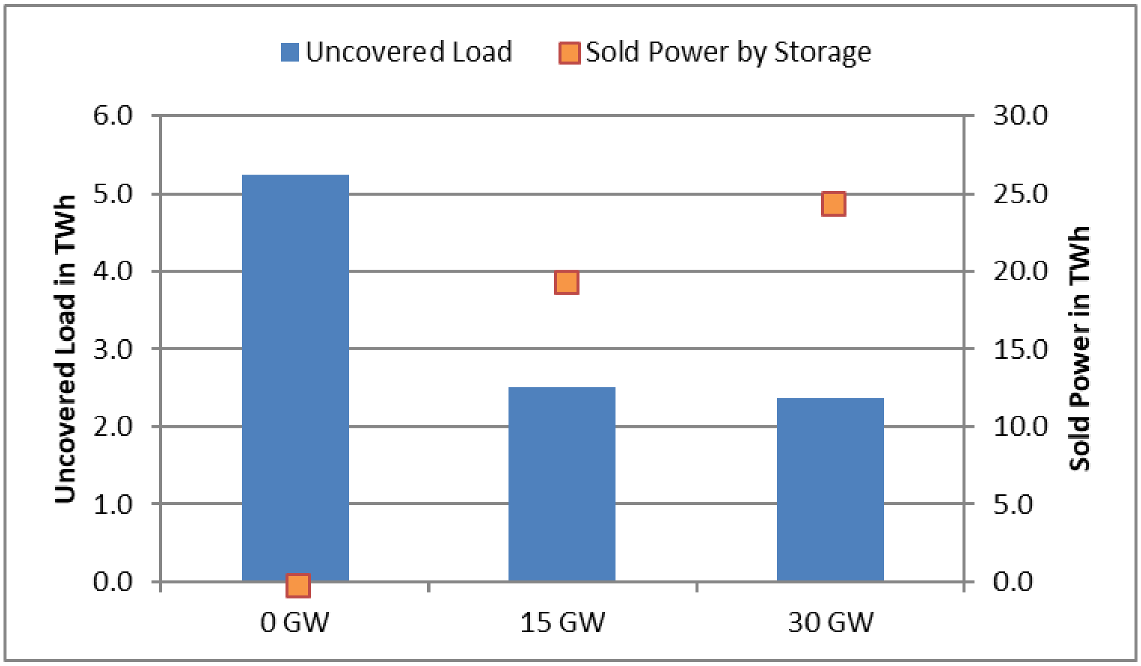

Figure 57: Uncovered load for 0 GW, 15 GW & 30 GW battery storage

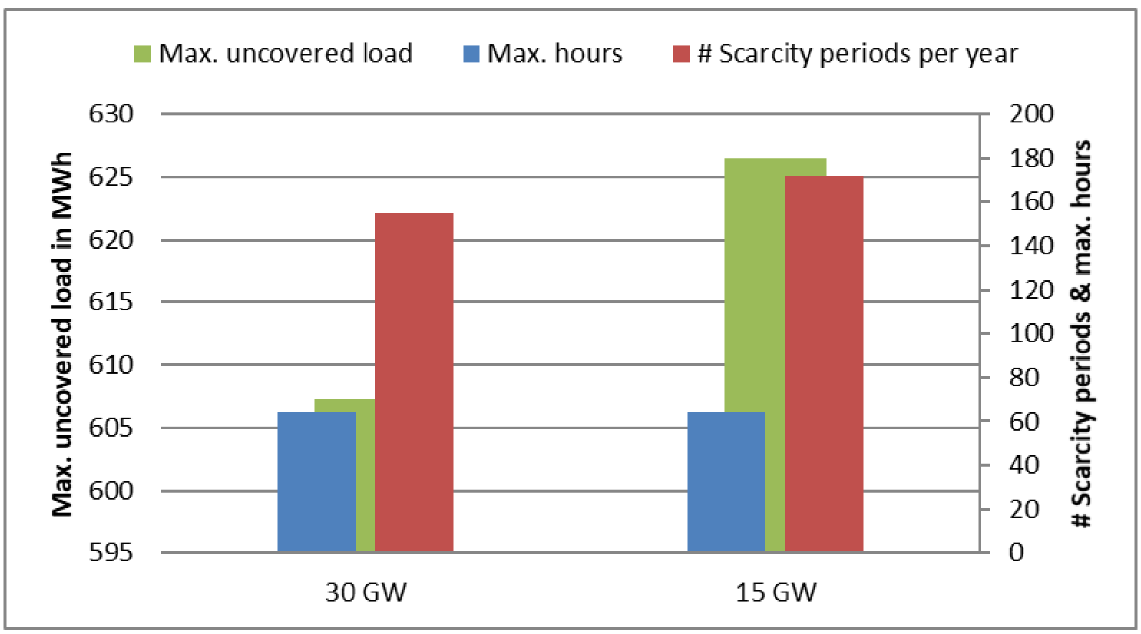

Figure 58: Overview of indicators for scarcity periods for 15 GW and 30 GW battery storage

The key question is why the doubled storage capacity does not have a stronger impact on the scarcity. Is the storage capacity with its technical restrictions not capable of addressing the sequence of scarcity moments? Or does the storage run the risk of reducing its profit by bridging more scarcity? The first question is addressed by the sensitivity analysis with the longer foresights. The second one is answered in the following.

Under the assumption sufficient energy is stored to cover the load in times of scarcity, the storage needs to deliberate whether it closes the gap between generation and demand, sells more energy but lowers the price or sells less to retain it. It depends on whether the profit by the additional sold energy can compensate the lowered price. The distribution of price in figure 59 shows that the scarcity price of 3 000 EUR/MWh is decreasing with more installed storage capacity.

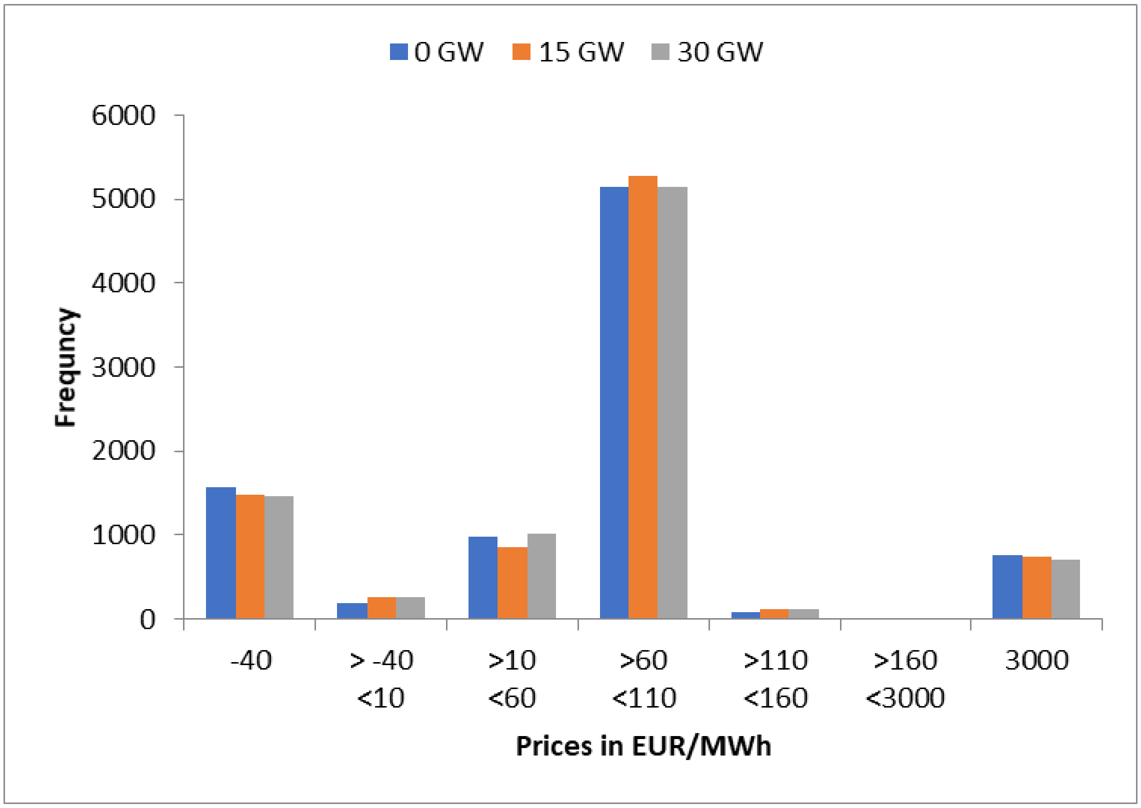

Figure 59: Distribution of prices for 0 GW, 15 GW and 30 GW battery storage

At the same time, the storage refuses to close the gaps between the residual load and its sold energy during several hours of the highest residual load (figure 60). Consequently, both bidding patterns in times of scarcity can be observed.

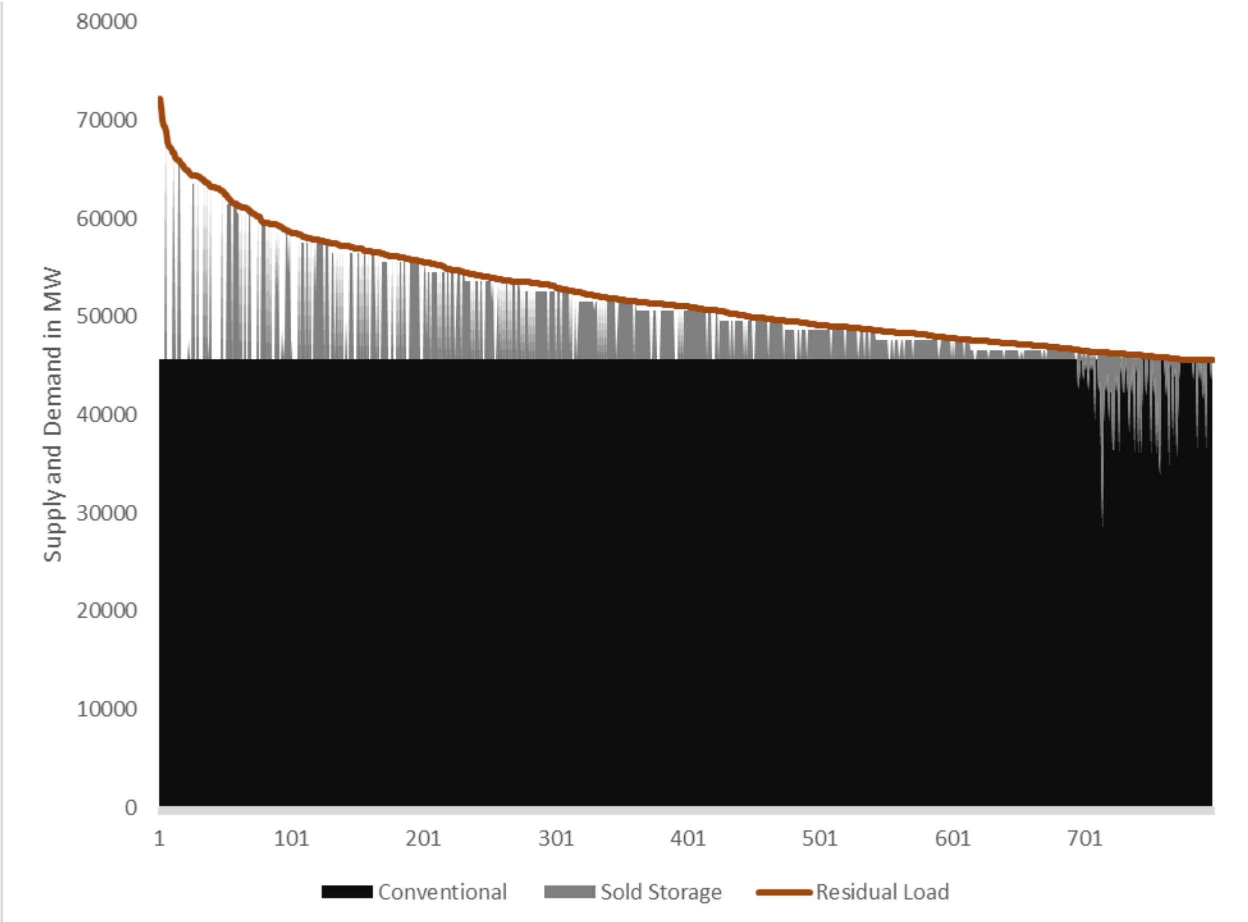

Figure 60: Residual load duration curve for the weather year 2010 and 30 GW storage

All in all, the small amount of restraint energy by the storage results in high prices for the consumers but it has only a minor effect on the level of uncovered load. The technical restrictions need to be analyzed further in the analysis of the longer foresight.

Similar like for the first experiment, the additional 15 GW storage has a minor impact on the cost recovery. The implementation of the additional 15 GW storage decreases the full load hours of the backup technology by 2 percent. The analysis in the previous chapter has shown that under the given conditions more installed storage capacity does not result in a significant increase in full load hours of the storages. Therefore, the additional 15 GW does not have the same impact on the full load hours of the gas turbine like the first 15 GW (see figure 61).

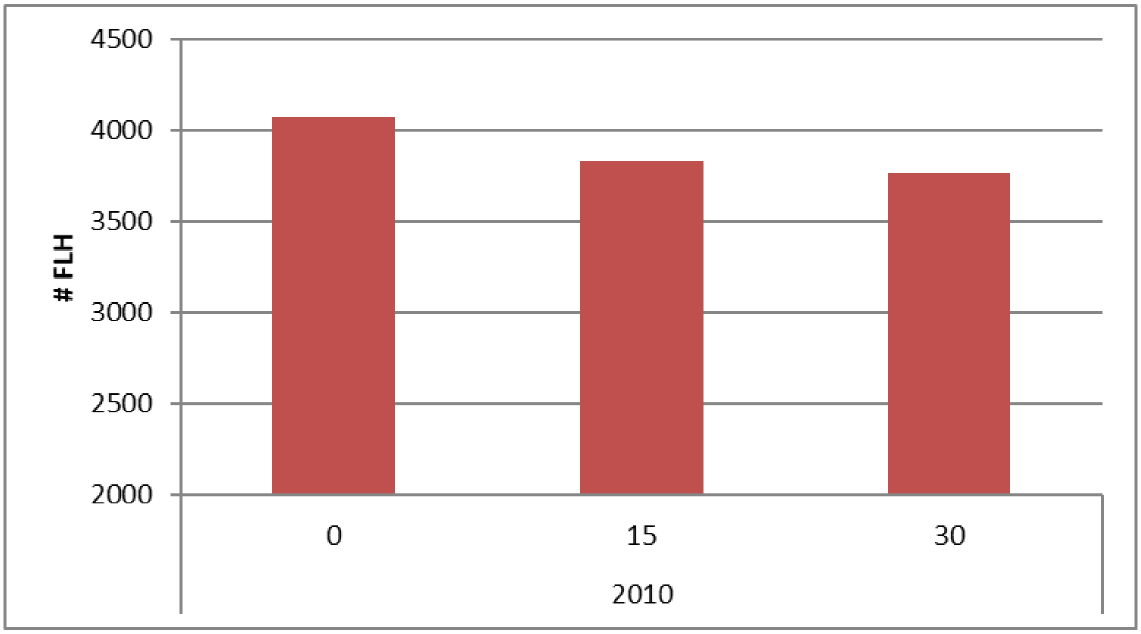

Figure 61: Full load hours for 0 GW, 15 GW and 30 GW battery storage

The prices higher than marginal costs of the gas turbine decrease only by additional 2.4 percent instead of the 6 percent like for the first installed 15 GW storage. Therefore, the margin is only 5 percent lower than for the reference case (see figure 62).

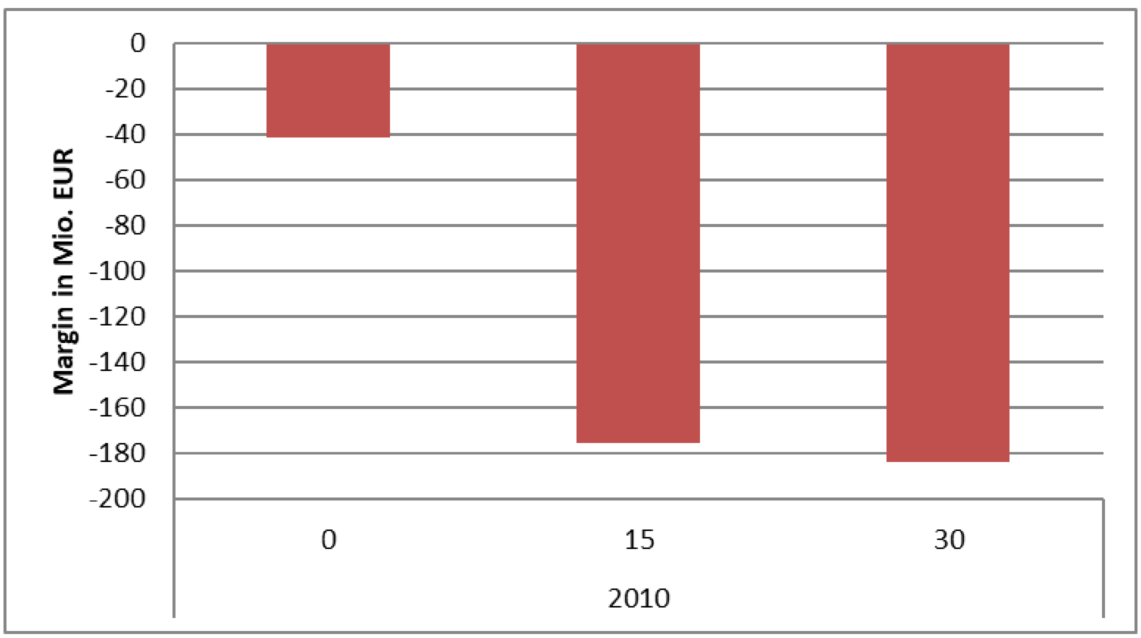

Figure 62: Profit margins for 0 GW, 15 GW and 30 GW battery storage

9.2 Longer Foresight for Battery Storage

The adaptation of the foresight impacts the way of bidding by the storage. With an increase of the foresight from one day to one week, the storage makes use of a higher number of hours with positive and negative extreme prices. At the same time, the utilized hours with prices higher than 160 EUR/MWh increase (see figure 64).

On the other hand, the sold energy by the storage and the utilized hours with low prices remain at a similar level (see figure 63). Consequently, the storage does not charge more energy in advance knowing that more attractive hours are about to come after the first 24 hours of the foresight, but it saves the stored energy for hours with higher prices. This indicates that the sequence of prices does not enable the bidding during more hours of low prices to address more hours with high prices in the foreseeable future.

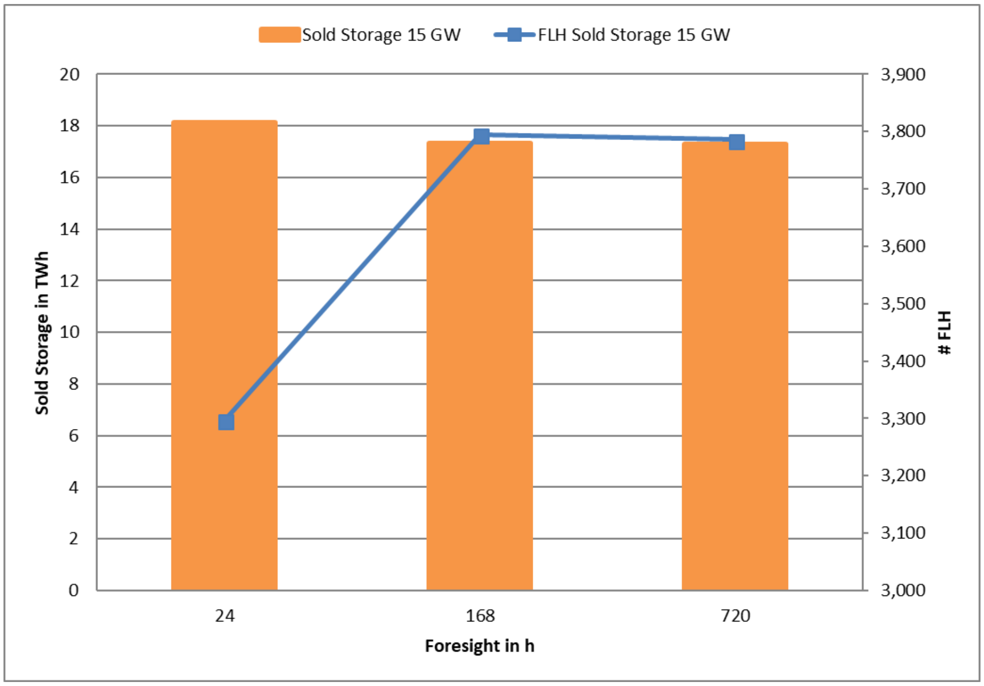

Figure 63: Full load hours of storage and sold energy by battery storage for a foresight of 24 h, 168 h and 720 h

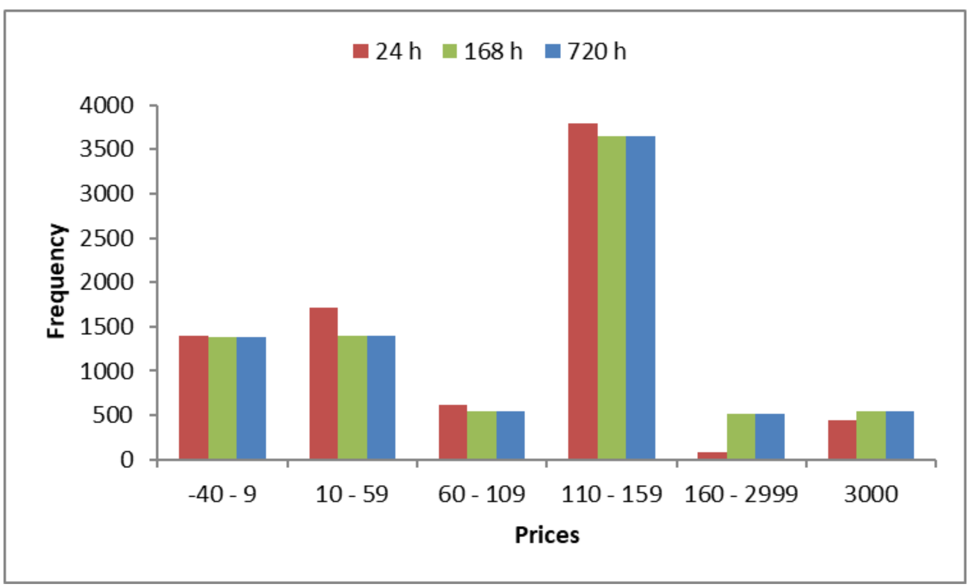

Figure 64: Distribution of storage bids in the context of prices for 15 GW battery storage for a foresight of 24 h, 168 h & 720 h

In figure 65, the behavior of the storage with 15 GW and 30 GW during hours of different prices is compared. The combination of the longer foresight and more installed capacity enables to not only capitalize on the prices higher than 160 EUR/MWh but also on more hours with a price higher than 110 EUR/MWh.

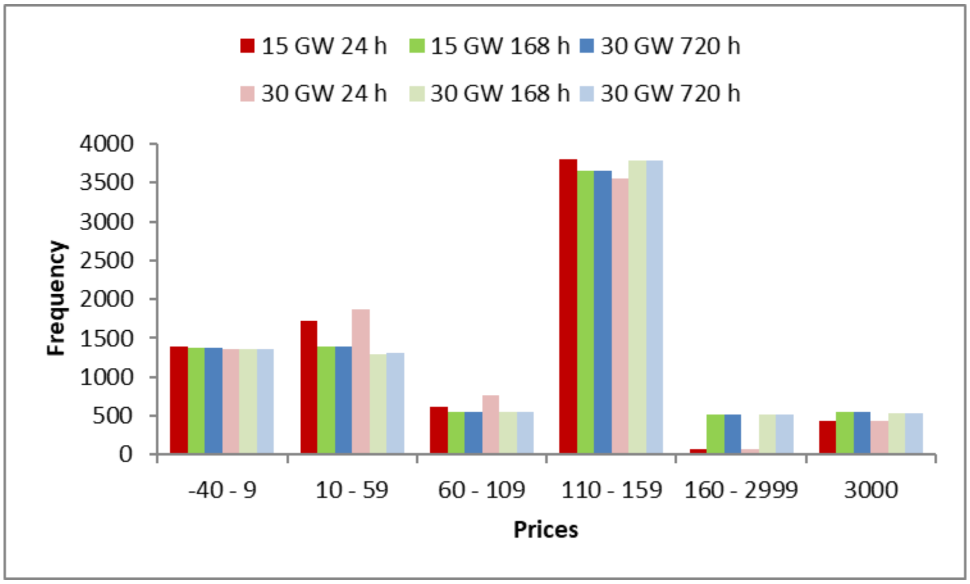

Figure 65: Distribution of storage bids in the context of prices for 15 GW and 30 GW battery storage for a foresight of 24 h, 168 h & 720 h

On the other hand, the more installed capacity leads to a lower number of hours with low prices in which the storage bids. The case of 15 GW demonstrates that more hours with low prices exist which could be used by the storage with 30 GW as well. As the storage with 30 GW does not charge during these hours, no need for additional stored energy during high prices exist within the foresight period of the negative prices. The behavior of the 30 GW storage underlines the mentioned causality that the sequence of prices does not enable the bidding during more hours of low prices to address more hours with high prices within a limited time span.

By increasing the foresight to one month, the selective behavior is enhanced. Without an increase in the sold energy or the full load hours, it manages to increase its income by choosing hours for charging and discharging with a higher price spread.

In the example of figure 68, the storage with a foresight of 720 hours decides to not sell its stored energy at the beginning of the period for ca. 70 EUR/MWh but saves it for hours with prices of 3 000 EUR/MWh at the end of the period. During these hours, the storage with the shorter foresight already needs to lower its bid because of the limited stored energy.

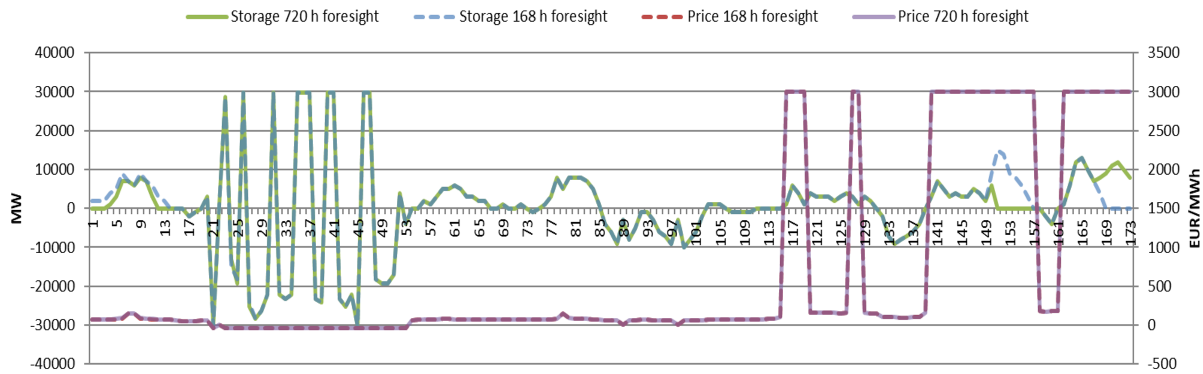

Figure 66: Example for bidding pattern of 30 GW battery storage with a foresight of 168 h and 720 h

The increasingly selective behavior does not contribute to a reduction of uncovered load. Whereas the uncovered load decreases by 25 percent for the change of the foresight from one day to one week, it stagnates for with switch from one week to one month. The uncovered load during the longest scarcity period decreases also only slightly by one percent comparing the foresight of one day and the longer ones (see figure 67).

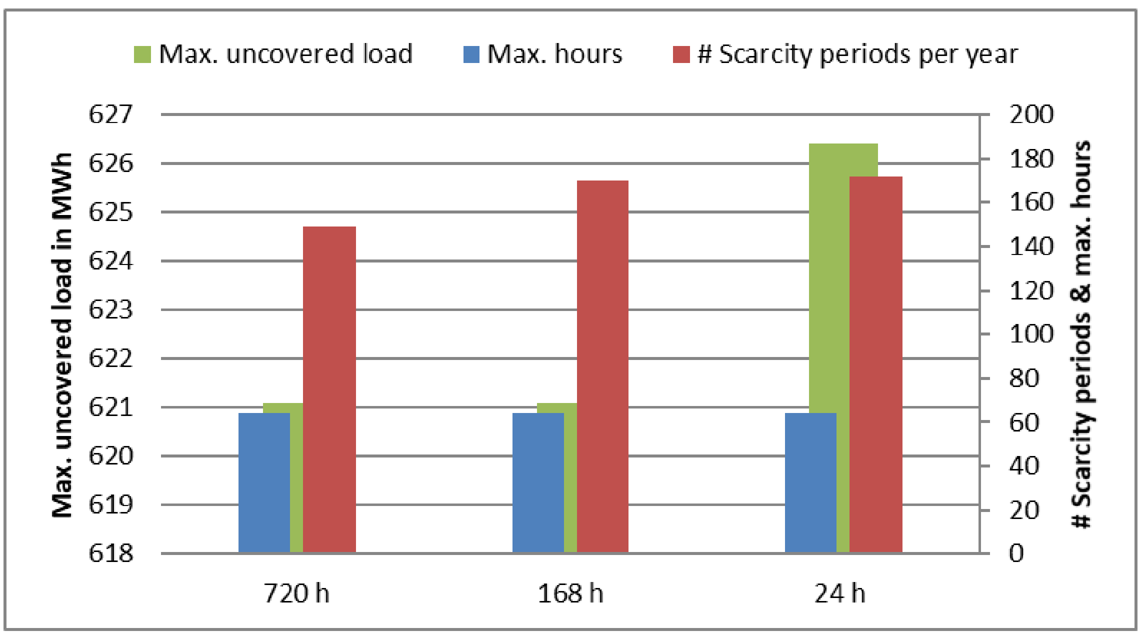

Figure 67: Overview of indicators for scarcity periods for 15 GW battery storage with a foresight of 24 h, 168 h and 720 h

In conclusion for the first experiment, battery storages have a natural limit for their contribution to maintain the security of supply. Beyond this point, more installed capacity or better forecasts with a longer foresight cannot substitute the investment in long-term flexibility providers.

Both longer foresights lead to a lower average price by 1.3 percent compared to the reference case for the second experiment. This results in a reduction of the backup margin of 24.6 percent and 31.3 percent.

9.3 Half Secured Capacity Gap

The reduced missing capacity[20] is directly translated into a reduction of the maximum scarcity peak to 16.8 GW. This radical effect is also observed for the uncovered load. The uncovered load of the longest scarcity period accounts only for 12 percent of the reference scenario. For the entire year, it accounts only for 6 percent of the reference scenario. The amount of scarcity prices is four times lower.

This sensitivity is not tested for the second experiment. As the selected backup technology is not differentiated between already installed and newly implemented unites, the adding of the other half of the missing installed capacity to the generation mix leads to the same results like for the reference scenario. At the same time, the backup capacity provider has an exceptional degree of market power in the second experiment which could be exploited. A decreasing capacity gap leads to a lower level of market power by the backup technologies.

9.4 Generation Mix with Additional 50 GW Photovoltaic

The additional 50 GW photovoltaic decrease the average price by 4 percent. This is not only triggered by the further decrease of the already low base prices, but also by reducing the extreme prices at the level of the price cap by 5 percent.

As illustrated in figure 68, the uncovered load p.a. is reduced by ca. 25 percent for the scenarios with storage and ca. 17 percent for the one without. At the same time, the hour and the level of the maximum uncovered peak remain the same (see figure 69). The time of the maximum peak is for both weather years during the late afternoon in winter, when the sun is about to set and only a little energy is provided by photovoltaic.

[20] Incl. a minor reduction due to the non-availability rate

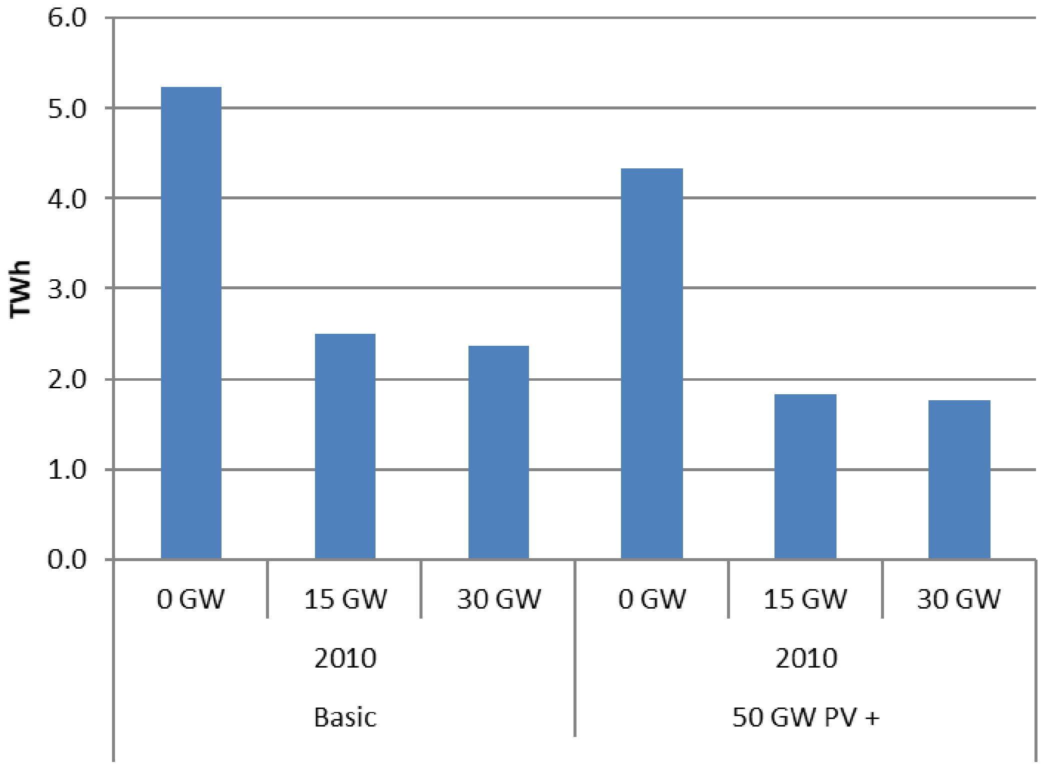

Figure 68: Uncovered load per year for basic renewable share and 50 GW PV +

The uncovered load of the longest scarcity period is decreased by 18 percent. The reduction is party directly connected to the coincidence of scarcity hours and the production of photovoltaic and partly because of the additional stored energy coming from photovoltaic.

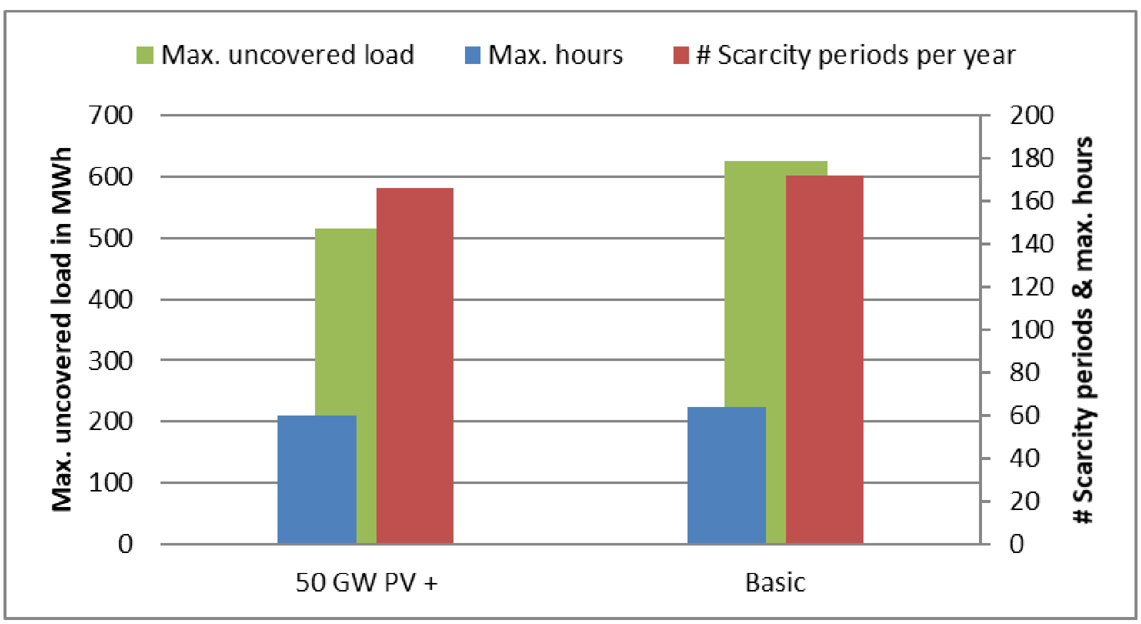

Figure 69: Overview of scarcity periods for basic renewable share and 50 GW PV +

By this additional energy provided by photovoltaic, the full load hours of the conventional power plants are further decreased. This can be seen in the load duration curve in appendix A. Compared to the basic scenario, the overall full load hours are reduced by 14 percent.

Even though additional photovoltaic capacity reduces the extreme prices and replaces conventional power plants, it only covers the load to a certain extent. The weather determined generation pattern of photovoltaic fits well with the daily demand pattern (see figure 70). As depicted in figure 53, it does not help to limit the seasonal differences in demand and supply (Lehmann et al., 2016). Additionally, the impact of uncertainty of weather on the electricity price and the full load hours of conventional power plants to recover their costs increases with the share of fluctuating renewables.

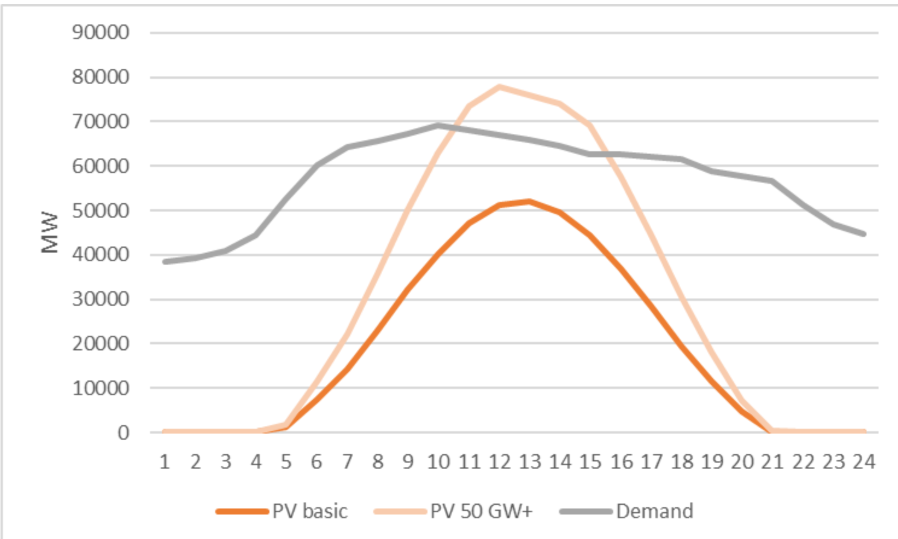

Figure 70: Daily generation pattern photovoltaic

For the second experiment, the additional 50 GW photovoltaic affect the margin of the gas power plant in two ways. It has an impact on the amount of sold energy by the backup technology and on the resulting dispatch price.

First of all, the full load hours of the gas turbine are further reduced. For the scenario without storage, the difference between both scenarios with and without the additional 50 GW photovoltaic comes from the number of full load hours of photovoltaic, which replace the gas turbine. For the scenarios with storage, not only the full load hours of photovoltaic, but also the ones by the storage replace the gas turbine. This reduction of the full load hours by the gas turbines is higher than in the basic scenario, as the increased photovoltaic gives the storage the option to load and sell more often (see figure 71).

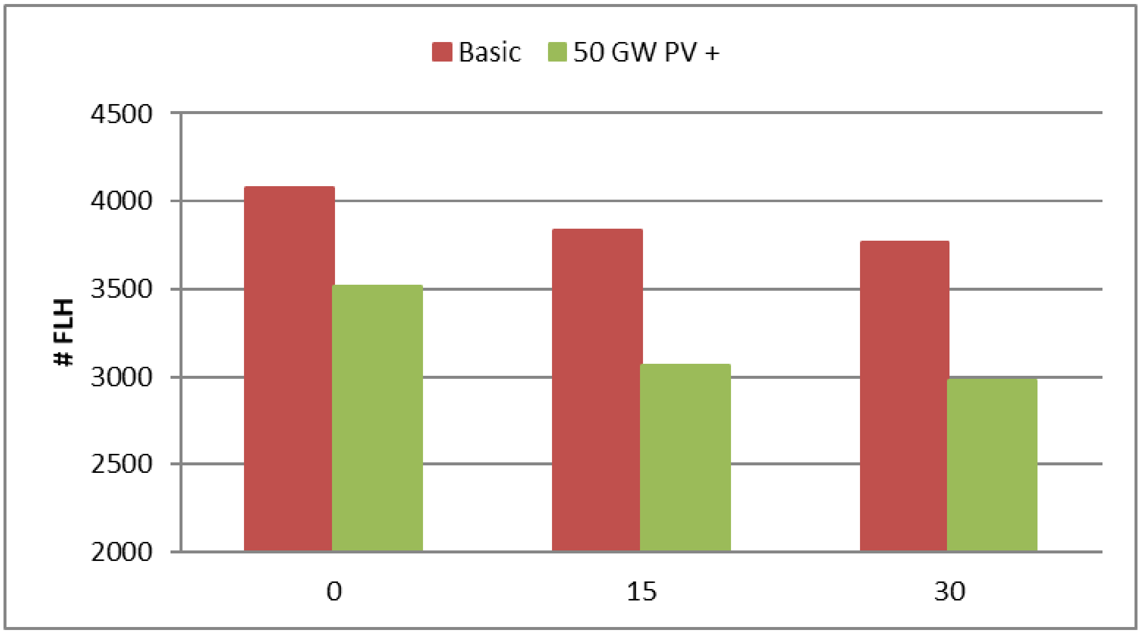

Figure 71: Full load hours of backup technology for basic renewable share and 50 GW PV +

The average price decreased by ca. 18 percent compared to the basic scenario. This is especially due to the high amount of negative prices, which increased by ca. 40 percent (see figure 72). Whereas the negative extreme prices only influence the usage of storage, the positive extreme prices influence the usage of storage and the gas turbines. The prices higher than the marginal costs of the gas turbine (75 EUR/MWh) decreased by ca. 19 percent. This has a negative effect on the full load hours of gas turbines.

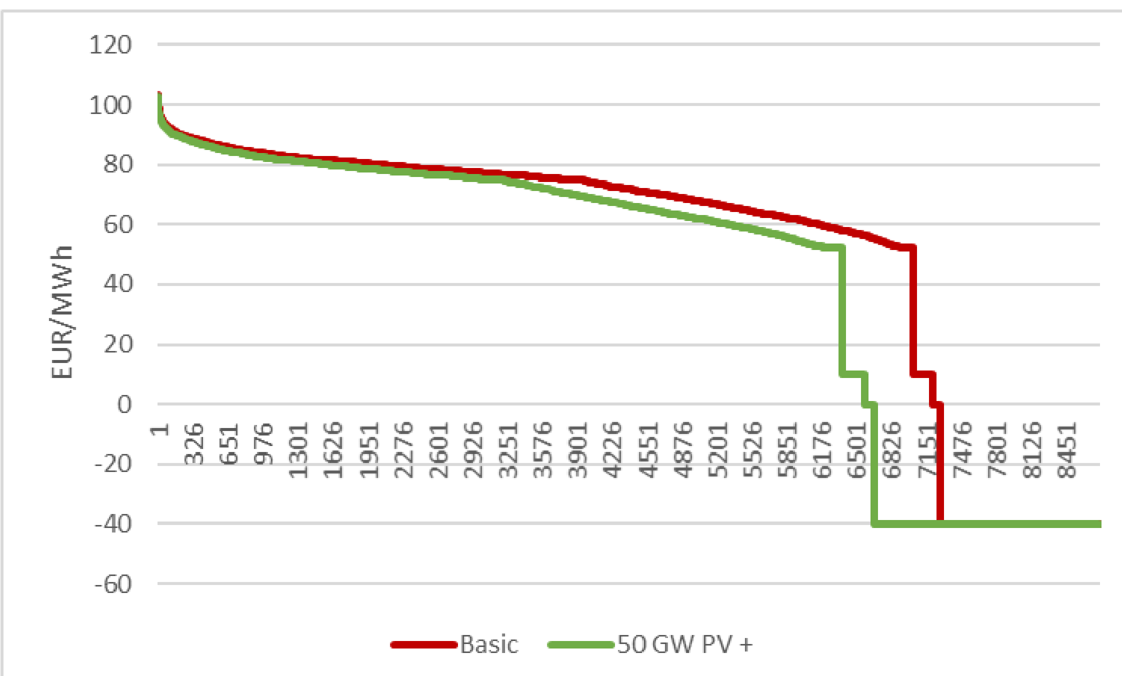

Figure 72: Price duration curve for basic renewable share and 50 GW PV +with backup capacity

The lower level of high prices and full load hours affect the cost recovery of the gas turbines significantly. For the scenario without storage, the negative margin is three times higher compared the basic scenario. For the ones with storage, it is 80 percent more (see figure 73).

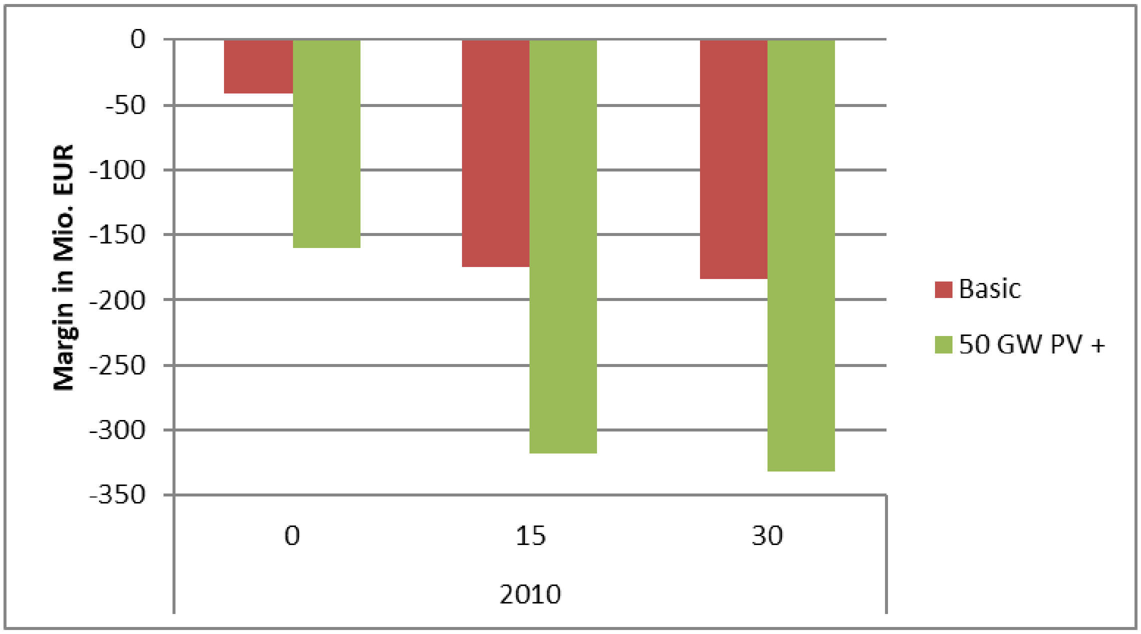

Figure 73: Profit margin of backup technology for basic renewable share and 50 GW PV +

9.5 Conclusion

The different configurations of the storage show a heterogeneous impact for the level of missing energy in the observation for the entire year. Whereas the uncovered load per year could be only reduced by 18 percent with the additional 15 GW battery storage, the combination of additional storage and a longer foresight leads to a decrease by 43 percent. The additional installed storage capacity could only show its real effect with the help of a longer foresight.

As the batteries already reached their technical limits in the Dunkelflaute with the shorter foresight, the foresight of one week does not add a real value in the extreme situation. The maximum scarcity peak remains at the same level and the uncovered load of the longest scarcity period decreases by 1 percent.

The determined level of investment restraints has a massive impact on the uncovered load. The maximum scarcity peak decreased as well by 36.6 percent. It can be concluded, that a strong reduced need of backup energy over the year does not results in an equivalent reduction of the maximum peak. Consequently, the cost recovery basis decreases stronger than the need of backup capacity in single hours. It remains open, whether the scarcity in single hours needs to be bridged by capital-intense investments in backup capacity or by other means, such as demand shedding.

Additional renewables deteriorate the margin of the backup technologies. Therefore, it is likely that a higher share of renewables leads to a lower level of secured capacity.

In conclusion, the sensitivity demonstrated that a higher level of installed short-term flexibility in combination with a longer foresight, less missing investments or a higher share of renewables mitigate the scarcity to some extent, but also deteriorate the business case for backup technologies (see figure 74).

	Scenarios	Experiment 1			Experiment 2	
		Uncovered load per year [TWh]	Maximum uncovered load [GW]	Max. consecutive uncovered load [MWh]	Average price with backup capacity [EUR/MWh]	Margin for backup technology [Mio. EUR]
Experiment	**Reference**	**2.5**	**26.5**	**626.4**	**52.7**	**-175.2**
	Mild Weather	-20.0%	-2.3%	-62.1%	-30.6%	-83.5%
	No Storage	+108.0%	0%	+11.0%	-0.6%	76.5%
Sensitivity	2 x Storage	-4.0%	0%	-3.1%	-0.8%	-4.6%
	1 Week Foresight	-20.0%	0%	-0.8%	-1.3%	-24.6%
	1 Month Foresight	-20.0%	0%	-0.8%	-1.3%	-31.3%
	50% less Investment Restraints	-94.0%	-36.6%	-88.1%	-	-
	Renewable Share like 2050	-28.0%	-1.1%	-17.7%	-18.0%	-80.9%

Figure 74: Summary of the sensitivity analysis – percentage express the difference compared to the reference scenario

10 Measures for an Improved Cost recovery of the Backup Technologies

Two main incentive for investing in backup technologies exist. It is either incited by the EoM in form of scarcity prices or by additional revenue stream from capacity mechanisms. For the first case, the operators of backup technology can exploit their dominant market position during scarcity times and bid more than their marginal costs by including markup in their bids.

This market-based option can be questioned for several reasons. First, it does not reduce the risk of price uncertainty for the investors. Second, other market participants benefit from the higher prices as well. The freeriding increases the costs for the consumers. As an alternative, the selected capacity mechanisms in chapter 4, capacity subscription, is evaluated.

For both options, the costs deficit from the second experiment is transferred into an additional revenue stream. It is assumed that the expectation of full cost recovery leads to investment into backup capacity and no scarcity[21] emerges anymore.

The costs of the energy supply are calculated for these two measures for cost recovery and the case of scarcity prices like in the first experiment. As the first experiment presents an extreme case, the costs for the sensitivity with the 50 percent smaller capacity gap are given as well. The comparison with the first

[21] Uncovered load in form of demand response is not considered as scarcity in this context.

experiment indicates the dimension of the financial burden for the consumer if the regulator decides to set investment incentives only by the scarcity prices of the EoM.

10.1 Cost Recovery by Markups

If you spread the uncovered costs over the awarded energy of the backup technology, a gas turbine would need to earn 6 EUR/MWh more in the reference scenario and 24 EUR/MWh in the scenario with the mild weather. For these numbers, it is assumed that the higher bids do not change the awarded energy.

It is neither likely that the awarded energy remains at the same level with higher bids nor can the markups simply be determined by the amount of intended extra income divided by the number of awarded energy. The complex process of developing markups for conventional power plants is demonstrated by (Rubin & Babcock, 2011). They consider the interdependences of the other power plants in case of an increase of the bidding price, the distribution of the spot market prices and uncertainties. Such an elaborated modeling of the markups is not possible in the course of the thesis.

In the following simplified calculation, the missing money aims to be covered by exhausting the dominant position of the gas turbine. Unrealistic assumptions, such as a joint price fixing agreement of all gas turbines and perfect knowledge about the price distribution, are accepted. The reciprocal effect of the bidding price and sold quantity is considered. A unified markup for the entire year is added for every bid of the gas turbine.

The simulation with the initially mentioned markups shows that the higher marginal costs result in a lower amount of awarded energy. This is especially due to the storages which adapt their bidding strategy facing higher wholesale market prices (see figure 75).

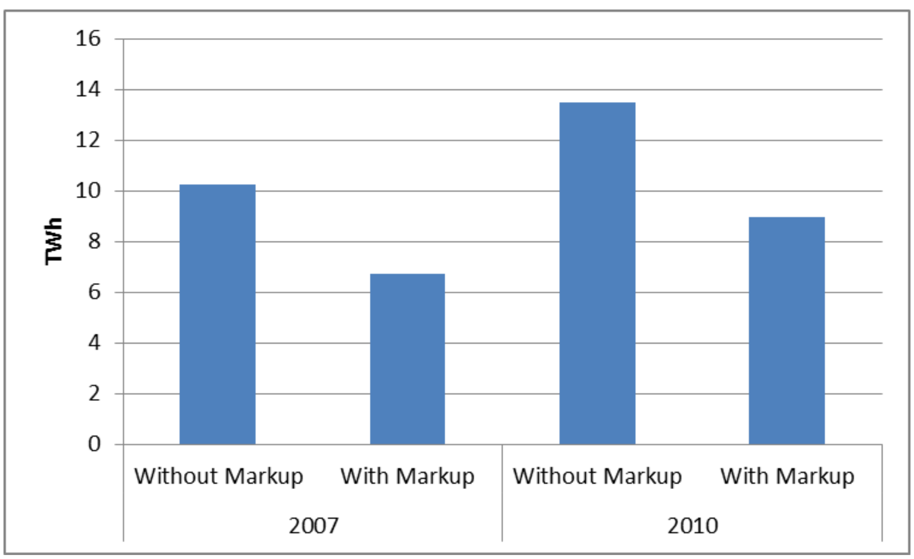

Figure 75: Sold energy of backup technology with and without Markups

A higher markup is needed to compensate for the smaller amount of awarded energy. For the weather year 2007, the margin becomes positive with a markup higher than 100 EUR/MWh. For the weather year 2010, the margin becomes positive with a markup higher than 70 EUR/MWh.

With the markup, the market prices increase by 20 (2010) and 33 percent (2007) on average per year. Not only the gas turbines profit from these higher prices, but the other market participants who are bidding during these hours. This leads to higher costs which need to be carried by the consumer. At the same time, it needs to be kept in mind, that the scenario without the additional gas turbine capacity and a high number of scarcity prices results in even higher costs for the consumers.

10.2 Cost Recovery by Capacity Subscriptions

A range of regulatory principles needs to be considered for the allocation of the costs of the backup technologies (Pérez-Arriaga, 2014). For example, the costs shall be allocated in an efficient way. This means that the one who benefits the most shall pay the highest share. By this, the users start to deliberate whether they would like to use the service and are willing to pay for it or not. Compared to other capacity mechanisms, the self-rationing of the capacity subscriptions especially reflects this principle.

As the focus of this thesis is set on the maintenance of security of supply in a cost-efficient way, the self-rationing and its efficiency enhancement are shown by the example of the reference scenario. The scope of this analysis is narrowed down to the German industry consumers, as they are the consumer group, which is most likely to activate their demand response potential first. The payments for the capacity subscription are calculated in a simplified way for this analysis.

44 percent of the total electricity p.a. in Germany is used by the industry (BMU, 2018). It is assumed that the industry contributes to that same share of the uncovered load in times of scarcity. To simplify the calculation, the actual consumption at the individual point of time is neglected[22]. For the industrial flexibility potential, the numbers about demand shedding by (Geipel, 2016) are used[23] (see figure 76).

Industry	Variable Costs	Demand Shedding Potential
	[EUR/MWh]	[MW]
Chlorine	248.00	395.00
Paper	276.00	2,407.00
Aluminium	402.00	1,081.00
Cement	445.00	769.00
Steal	616.00	1,649.00
Sum		6,301.00

Figure 76: Overview of industrial demand shedding potential and its costs

The decision to use capacity subscription or reduce the consumption in scarcity moments depends on technical and economic considerations. First of all, it is checked to which extent the flexible part of the

[22] The scarcity moments happen to different moments in time. For instance, the same share of scarcity hours occurs during business hours (8:00 to 18:00) than before and after business hours in the reference scenario. The patterns of the scarcity and the contribution by the different consumer groups is a subject of further research.
[23] Whereas the shedding can be done for four hours, the duration of the shifting ranges between 1.5 and 3 hours. Due to the better match of the long scarcity periods, the analysis focuses on demand shedding.

consumption can be used to lower the uncovered load in scarcity hours[24]. Assuming that 44 percent of the uncovered peak consumption is requested by the industry, the ca. 6.3 GW of demand shedding potential is not sufficient to cover the 11.7 GW (2010) or 11.4 GW (2007) industrial peak. Therefore, the industry needs to request 5.4 GW (2010) or 5.1 GW (2007) of capacity subscriptions due to technical limitations. Assuming that the industry is the only consumer who decides to adapt their consumption instead of purchasing capacity subscriptions, the backup technology is going to sell certainly 19.6 GW (2007) and 20.2 GW (2010) capacity subscriptions. These certain sales are used as a basis to calculate the payments for each capacity subscription in the following step. By this, the recovery of the missing money is ensured.

Secondly, the costs of lowering the consumption and the payments of the capacity subscriptions are compared. In the course of the simplified capacity subscription calculation, the uncovered costs of the backup technologies for the reference scenario and the scenario with the mild weather year is divided by the share of the certain sales of the maximum uncovered peak. This is results in payments of 8.7 Mio. EUR/GW (2010) and 16.4 Mio. EUR/GW (2007). If the backup technology sells more than the certain sales of 19.6 GW and 20.2 GW, they earn additional profits.

To compare the costs of both bridging options, the price per covered GW of the capacity subscription (C_{CS}) is compared to the usage of the demand shedding and its costs ($C_{DS\,t}$ (u_{cs})). The overall costs for the industry ($C(u_{cs})$) aims to be minimized considering the constraint that the obligation of bridging the uncovered load needs to be fulfilled ($\sum_{t=1}^{T} l_{t\,0} + \mathrm{u}_{\mathrm{CS}} = \sum_{t=1}^{T} \sum_{i=0}^{I} \Delta\, l_{\mathrm{i}} + \mathrm{u}_{\mathrm{CS}}$). This is expressed by the formula 10.2.1. The optimum amount of capacity subscriptions (u_{cs}) is determined by excel solver.

(10.2.1)

$$Min\ C(u_{\mathrm{CS}})$$

$$C(u_{\mathrm{CS}}) = Ccs * u_{\mathrm{CS}} + \sum_{t=1}^{T} C_{\mathrm{DS\,t}}(u_{\mathrm{CS}})$$

$$C_{\mathrm{DS\,t}}(u_{\mathrm{CS}}) = \sum_{i=0}^{I} \Delta\, l_{\mathrm{t\,i}} * C_{\mathrm{DS\,i}}$$

$$\text{s.t.} \sum_{t=1}^{T} l_{\mathrm{t\,0}} + \mathrm{u}_{\mathrm{CS}} = \sum_{t=1}^{T} \sum_{i=0}^{I} \Delta\, l_{\mathrm{i}} + \mathrm{u}_{\mathrm{CS}}$$

This optimization problem results in an additional request of 3.4 GW (2010) and 2.8 GW (2007) for the capacity subscription. As the payment for 2007 is two times higher than the payment for 2010, more demand shedding is activated for 2007. The most expensive used demand shedding potential is the one by the aluminum industry. For 2010, it was used in one hour and for 2007, in two hours. Looking at the

[24] All demand can be lowered for a certain price. This can be the offered price of the demand response services or in the extreme case the value of lost load. As the value of lost load is significantly higher than the payments of the capacity subscriptions, this extreme case is not considered in this context.

total avoided consumption p.a., 2.2 times more demand shedding is used for 2007 than for 2010. The maximum capacity is 3.8 GW for 2007 and 2.9 GW for 2010 (see figure 77 and 78).

A duplication of the price for capacity subscription in the reference scenario leads to similar costs, as the higher capacity subscription price is compensation by a lower quantity and more demand shedding.

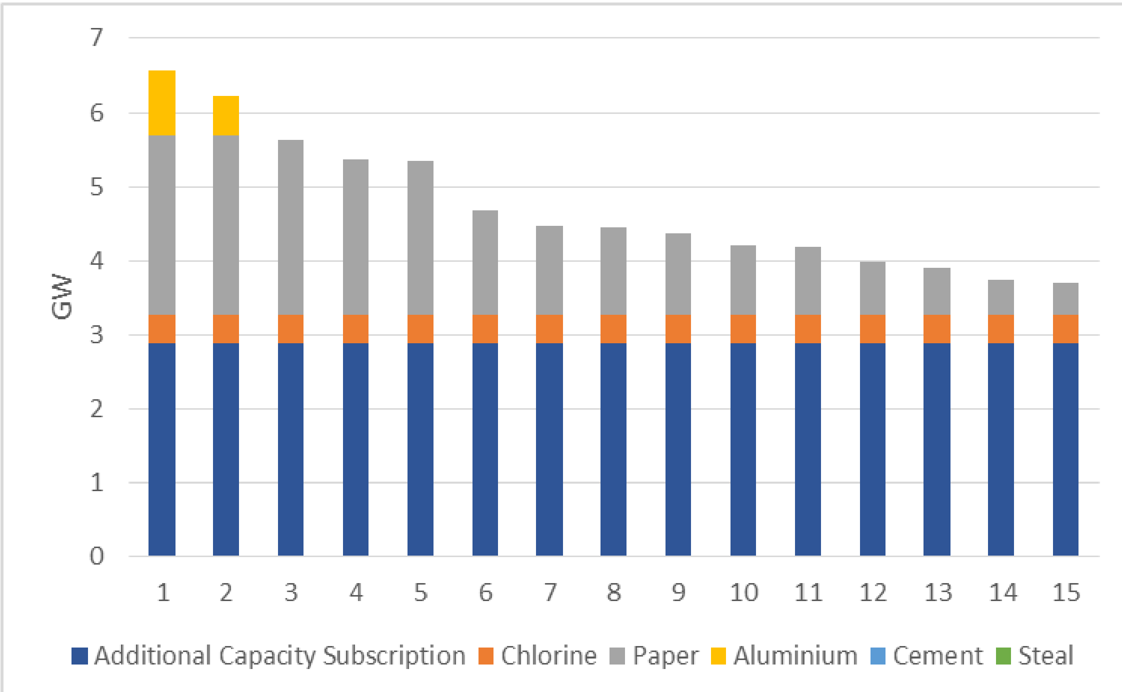

Figure 77: Optimal mix of demand shedding and capacity subscriptions for weather year 2007 and 15 GW battery storage

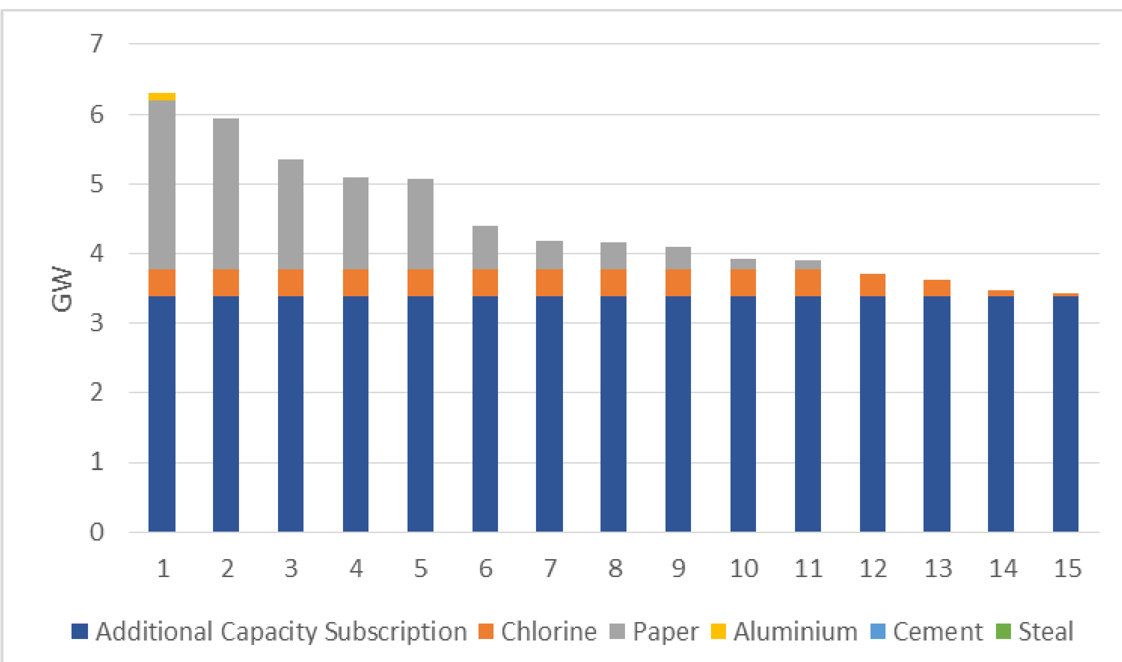

Figure 78: Optimal mix of demand shedding and capacity subscription for weather year 2010 and 15 GW battery storage

The results can be seen as an indicator for the efficiency enhancement by the self-rationing approach of the capacity subscriptions. It needs to be taken into account, that the payments only reflect the uncovered costs of one year and that no sophisticated allocation mechanisms are used. Additionally, the shown demand shedding potential could be used at the wholesale market. For the experiments, no demand shedding is implemented. If a partly flexible demand is implemented in the simulation, the demand shedding which is implemented at the wholesale market would lower the needed backup capacity and change the request for capacity subscriptions.

10.3 Costs of Energy Supply for the Consumer in Case of Scarcity

A higher number of scarcity prices of 3 000 EUR/MWh lead to high average costs per year. In the reference scenario, the average price is 306 EUR/MWh with 749 scarcity hours. In case of the sensitivity with 50 percent less secured capacity missing, the average price is 118 EUR/MWh with 193 scarcity hours. Multiplying the hourly price with the hourly awarded energy, the total costs for the energy supply are 170.6 bn. Euro for the reference scenario and 68.8 bn. Euro for its sensitivity.

Not only the costs but also the uncovered load and the connected discomfort is relevant for the consumer. The reference scenario does not manage to serve 0.5 percent of the yearly demand. For its sensitivity, 0.03 percent. In the literature, a value for every MWh of non-served load is determined, which reflects the discomfort for the consumer. As the value is not considered in the costs overview, the presented costs are conservative.

10.4 Conclusion

On the political and academic level, the fundamental decision is discussed whether the invisible hand of the market shall set the incentives for investments in backup capacity or whether a regulatory intervention shall protect the consumer against the scarcity prices. The analysis of chapter 10 can neither answer this fundamental question nor estimate market dynamics or the financial incentives which are needed to trigger investments. Nevertheless, it can give an indication about the financial burden for the consumer, which can be prevented by a regulatory intervention in form of a well-design capacity subscription. Even if the scarcity prices are sufficient to trigger investments, the high financial burden of the scarcity prices need to be at least borne by the consumers in the lead time between the investment decision and commission of the flexibility provider.

In case of the extreme scarcity by the reference scenario, the supply costs are 12.9 times higher than in the scenario with the implementation of the capacity subscription. In the case of 50 percent less missing capacity, the costs are 5.2 times higher.

The uncovered load due to the activated demand shedding by the capacity subscription is higher than in the sensitivity scenario but lower than the reference scenario. At the same time, it needs to be considered that the industrial consumers make the decision of demand shedding by themselves and that the costs of demand shedding are included in the overview of figure 79.

In this simplified representation of reality, the consumers have the highest quality of supply at the lowest cost in the case of a market with a capacity subscription.

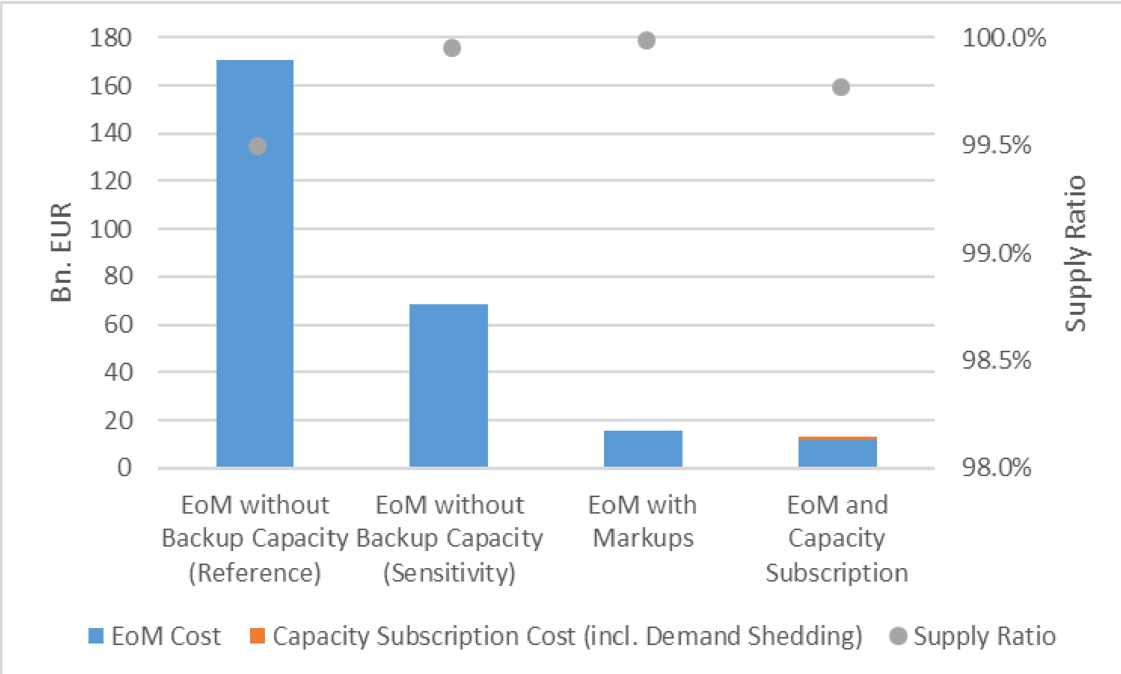

Figure 79: Supply ratio and total costs of energy supply for different combinations of EoM and measures for cost recovery improvement

11 Results

The analyses of the thesis are like jigsaw pieces which create a full picture once they are composed. Their composition addresses the main research question “How to maintain the security of supply under extreme weather conditions in a renewable dominated electricity system in the most cost-efficient way?”. The underlying knowledge gap about the impact of the uncertain weather conditions and the available short-term flexibility on the cost recovery of backup technologies is investigated. Thereby, not only the issue of a lacking cost recovery is presented but also measure to improve it.

In this chapter, the results are summarized and confronted with the four hypotheses which shape the investigations of the thesis. The subsequent chapter aims to interpret and discuss the outcome critically.

1. ***The level of scarcity varies substantially with the weather conditions***

The agent-based model AMIRIS is used to determine the level of scarcity for an electricity system with a high share of renewables and missing secured capacity and the income of backup technology, which is dimensioned to bridge the scarcity. The three established scarcity indicators give a heterogeneous picture. On the one hand, the level of the scarcity peak is similar for all scenarios. This implies that single hours with high residual load and no available short-term flexibility can occur regardless of the selected weather year or availability of battery storage. On the other hand, the aggregated uncovered load strongly varies for the different weather years and battery constellations. 25 percent more energy is needed to cover the supply gap in the extreme weather year than in the mild one.

The severity of scarcity becomes explicit by looking at the uncovered load of the longest scarcity period of each simulated year. Three times more energy needs to be covered by backup capacity in the extreme weather year than in the mild one. This scarcity lasts for almost three days and contains 0.25 percent of the yearly uncovered load. The period by mid-February includes the maximum peak of uncovered load and is surrounded by other long scarcity periods. In this sense, it is a stress test for the electricity system.

2. ***The short-term flexibility providers lower the need for backup capacity but cannot substitute it***

The emergence of battery storage is a mixed blessing for the security of supply. It divides the uncovered load per year in a half. At the same time, it deteriorates the cost recovery conditions for the backup capacity without being an adequate substitute for it. It can hardly address situations of extreme scarcity solely. Looking at the contribution by battery storage to lower the uncovered load in the longest scarcity period, they only lower the uncovered load by ca. 10 percent. The maximum uncovered load cannot be reduced at all by the battery storage.

The correlation of extreme scarcity peaks and long scarcity periods gives the battery storage hardly any opportunity to charge during the extreme scarcity periods. For instance, more than one-third of the extreme peaks (in this case defined as 20 GW and more) is surrounded by a period of scarcity of 5 hours and longer.

The knowledge about future prices impacts the ability of the battery storage to address scarcity hours. If the so-called foresight is extended from one day to one week, the uncovered load per year is reduced by 20 percent. The positive effect of the longer foresight is bounded by the technical limitations of the battery storage. In the presented scenarios, no additional mitigation of the scarcity can be achieved in times of the Dunkelflaute by a foresight of one week. Also, a longer foresight than one week cannot reduce the uncovered load per year further.

The eligibility of the price sequences to support the bidding of the storage can be inferred by the foresight analysis. It is noticeable that the longer foresight increases the number of used high prices but does not have the same effect on the low prices. Upcoming high prices seem to be missing to create an additional value by charging more energy during the low prices. This indicates a limited fit of the prices sequences for the charging and discharging of the battery storage.

All in all, the short-term flexibility providers are restricted by their technical limitations and the sequence of market prices. Despite their positive effect on scarcity, they cannot substitute long-term backup technologies.

3. ***The level of cost recovery for backup technologies on the EoM is not sufficient and depends strongly on the weather conditions and the availability of battery storage***

Due to its ability to react fast to scarcity signals and its relatively low fixed costs, gas turbines supplied with fossil gas are selected as backup technology. The maximum scarcity peak indicates the level of backup capacity. The combination of a similar maximum peak for every scenario and the divergent levels of requested backup energy give already a negative indicator of the cost recovery of the backup technology. This is proven by the second experiment. Under the assumption that the backup technology does not leverage its market power during scarcity times, its cost cannot be covered. Referring to the scenario with the highest likeness of cost recovery, the one without storage and extreme weather, the implementation of battery storage lowers the profit margin by four times. The mild weather conditions of 2007 lower it two times further.

Due to limitations of the model, power-to-methane is not simulated as backup technology, but the insights from the simulation with the gas turbine are transferred in a simplified calculation. It results in a higher (but still negative) profit margin for power-to-methane.

Two aspects need to be considered in this context. First, the transfer of the income of the fossil gas technology is a simplified calculation which ignores the complexity of charging and discharging of power-to-methane. Second, gas turbines supplied with fossil gas have a lower fixed costs share than the ones supplied with synthetic methane. Therefore, fossil gas applications can better adapt to the changing and uncertain request of energy.

It is likely that a further expansion of renewables leads to a larger price spread and a more constant level of scarcity. In this context, power-to-methane becomes an interesting backup option. A two-stage approach is recommended. First, a gas turbine supplied with fossil gas is implemented as backup technology and with a stabilization of scarcity, the source of gas is replaced by synthetic methane from a power-to-methane entity.

Solely the availability of suitable backup technologies will not lead to investments without a positive business case. Therefore, some measures to handle the lacking cost recovery are presented in the next paragraph.

4. ***A well-designed regulatory intervention which rewards the contribution to the security of supply can reduce the costs for the consumer and improves the supply ratio***

Either way, the circumstances for the investments in both backup technologies are uncertain. The literature foresees two possible constellations for investments in backup technologies. It is either triggered by the EoM in form of scarcity prices, markups and high risk premiums for the investors or by an additional revenue flow for its contribution to the security of supply. The later reduces the risk of cost recovery and stimulates investments. Security of supply is considered as a public good which is not priced so far. A regulatory intervention needs to organize the pricing of this good (Cremer, 2013). This kind of intervention is called capacity mechanism.

If a capacity mechanism does not only trigger investments in backup capacity but incites a system friendly behavior by all market participants, the security of supply can be maintained in the most cost-efficient way. In this sense, the MCDA highlights the concept of capacity subscriptions. By its self-rationing approach, it gives the consumers the option to decide whether they prefer to invest into backup capacity or contribute to the security of supply by reducing their consumption at peak times. The self-rationing activates demand response potentials and enhances efficiency. In the simplified calculation of the capacity subscriptions for industrial consumers, 46 percent of the technical demand response potential are activated by the capacity subscription.

As an alternative way for improving the cost recovery, backup technologies can exhaust their dominant market position in scarcity times by including markups in their bids. As other market participants benefit from the increased prices as well, the measure with markups leads to higher costs of the energy supply for the consumers than the one with capacity subscriptions.

Comparing the costs of energy supply in case of the EoM with and without sufficient secured capacity, the acceptance of scarcity prices leads to significantly higher costs for the consumer every year. Assuming that the scarcity prices would trigger investments in backup capacity, this higher financial burden would last at least during the lead time between the investment decision and commissioning of the backup technology. For the simplified calculation, the costs of energy supply are 12.9 times higher in the extreme case of scarcity and 5.2 times higher for a sensitivity of only 50 percent of the missing secured capacity.

The simplified calculations demonstrated the efficiency enhancement by the capacity subscription and the mitigation of the financial burden for the consumers by not accepting scarcity prices. At the same time, it needs to be considered, that the market dynamics for investments and the design of a well-tailored regulatory intervention are complex. This complexity is not reflected in the thesis. Therefore, the last hypothesis is the least substantiated one by the investigation compared to the other three. Its drawbacks and possible improvements are discussed further in the next chapter.

In conclusion, the thesis shows that suitable backup technologies are available and needed in an electricity system with a high share of renewables. At the same time, no secured cost recovery can be guaranteed by the unpredictable market conditions, which depend strongly on the weather conditions and availability of short-term flexibility. The concept of capacity subscriptions is recommended as a measure to improve the costs recovery and enhance efficiency.

12 Discussion and Interpretation

The thesis is shaped by the four hypotheses established in chapter 1 and aims to close the knowledge gap about the cost recovery of backup technologies depending on weather conditions and battery storage. Its attainment and the subjects of further research are reflected in the following. Thereby, the alignment of the conducted research and the hypotheses, the shortages of the methodology and remaining aspects of the research question are discussed critically.

12.1 The Impact of Weather on the Security of Supply

The three presented indicators enable an evaluation of different scarcity incidents and the selection of a mild and extreme weather year. The same weather years are rated as mild and extreme by Fraunhofer IEE, 2018. The weather year analysis by Fraunhofer IEE, 2018, Huneke et al., 2017 and this thesis have a common shortcoming. By highlighting the mildest and most extreme weather year, the range of possible outcomes is provided, but no realistic view of the future weather developments and their yearly sequence. An in deep analysis of long-term weather forecasts is subject to further research.

Furthermore, the presented scarcity indicators identify the most apparent scarcity moments but do not provide a complete picture of the scarcity. Simplified indicators have the dilemma that they either focus on a single moment and neglect following scarcity issues or aggregate scarcity over a longer period and dilute the magnitude of the single events. For instance, the relative differences between the reference scenario and the alternative ones are more extreme for the uncovered load of the longest scarcity period than for the uncovered load over the whole year. The longer duration involves more moments without scarcity and dilutes the effect. An analysis of the sequences of scarcity periods and the duration between them would complement the understanding about scarcity.

It is demonstrated that the coincidence of the scarcity indicators is a special challenge for the security of supply. Beyond that, the single indicators are not weighted according to their impact on the security of supply. Different forms of flexibility are eligible for different forms as scarcity. Scarcity incidents start to become critical if no eligible flexibility form is available. The proposed further investigation about the overall potential of short-term flexibility in the previous paragraph can be supplemented by a comparison of these potentials and the presented scarcity moments.

12.2 The Impact of Battery Storage on the Security of Supply

The simulated participation of battery storages on the wholesale market is a mixed blessing for the security of supply. On the one hand, they contribute to cover the load and level off extreme prices. On the other hand, they diminish the investment basis of backup technologies and make investment more unlikely. Four distinctions need to be made assessing the transferability of the simulation results on the real impact of battery storage on the security of supply.

First of all, the ownership and operation of battery storage are likely to be spread over a heterogeneous set of actors. A competitive environment of storages will be created in real life. In contrast to that, the storage is modeled as a monopoly of flexibility in most literature and in AMIRIS. It optimizes its arbitrary strategy without the need of considering the bids by other flexibility providers, which use an arbitrary strategy as well (He et al., 2016; Majidi et al., 2017). The core issue of representing a competitive environment for storages is the condensation of several independent arbitrary strategies. A game theoretical approach needs to be used (Y. Wang, Ai, Tan, Yan, & Shuting, 2015). The main drawback of this monopolistic representation of the storage is that it maximizes its profit in some hours by restraining the stored energy to keep the market price on a high level. In a competitive environment, it is unlikely that the independent bids by the different storage operators result in the exact amount of energy to use the high price without lowering them. As the price is likely to be lowered anyway, the storages create profit by selling their stored energy instead of holding it back. Therefore, scarcity moments tend to occur less frequently and with a lower magnitude in a competitive environment than in the simulation.

Second, it is demonstrated by the simulation that a higher foresight lead to a higher profit for the storage. The realistic level of foresight is debatable. Most publications (e.g. Sioshansi et al., 2009) indicate a range of outcomes with different foresights. With more available data and better forecasts over time, the foresight will improve. Additionally, no forecasting errors impacted the foresight in the simulation. The implementation of randomized forecasting errors would make the simulation more realistic.

Third, it is assumed that the availability of the storage is not limited within the scope of their technical possibilities. In the course of sectoral coupling, flexibility shall be provided by applications whose main use case is not the trading of energy on the wholesale market. Those are, for instance, electrical heaters or electric cars. Their limited availability would reduce the contribution to the security of supply. The temporal coincidence of their non-availability and scarcity moments is a subject of further research.

Fourth, the simulation aims to demonstrate the contribution of battery storages during different scarcity events. Two kinds of scarcities cannot be addressed by battery storages. On the one hand, their limited energy-to-power ratio and capacity can hardly handle the coincidence of high scarcity peaks and longer scarcity periods. On the other hand, the storage needs volatile prices within one foresight period to charge and discharge. The storage becomes inactive for a long sequence of only high or low prices. The existence of such price sequences is only proven by the particularity that the storage with more capacity uses less negative hours to charge than the one with less capacity, as no more stored energy is needed at the given moment. The eligibility of price sequences for the bidding of battery storages is subject of further research.

Starting with the impact of battery storage on the security of supply, the research about the contribution of short-term flexibility is not exhausted so far. (D'haeseleer, De Vries, Kang, & Delarue, 2017) presents a range of other providers than battery storage (e.g. demand response). The on-going digitalization provides new insights about flexibility potentials and instruments to leverage it. For instance, (Fraunhofer IEE, 2018) demonstrates how a high degree of sectoral coupling minimizes the need for conventional backup capacity. A well-coordinated ensemble of short-term flexibility can help to maintain security of supply.

12.3 Backup Technologies in the Energy-Only-Market

The presented scarcity incidents depend on the implemented generation mix and especially the missing secured capacity. The generation mix is determined exogenously in AMIRIS. The self-determined level of investment restraints is susceptible. More or less missing capacity would lead to a different level of scarcity. Alternatively, an optimization model could determine an optimized generation mix according to an optimization objective (e.g. minimize system costs) and considering constraints. This approach neglects the investment decisions and possible investment restraints by actors on the micro level. Missing investments are a key underlying assumption of the research questions. Therefore, a model which enables the simulation of restrained investment and scarcity is selected. The impact of fewer investment restraints is tested as a sensitivity.

Deissenroth et al., 2017 discuss the gap between optimal and real market outcomes. Simulations and optimizations have advantages and drawbacks as a methodology. The modular structure of agent-based models allows combining both. For this investigation, only the storage agent is empowered to make decisions to maximize its profit. More agents which are enabled to make decisions according to their optimization objective (e.g. investment decisions to maximize their profit) would lead to a more realistic outcome. Due to time constraints, this was not possible.

(Huneke et al., 2017) bypasses the issue of determining a realistic level of missing investments by not considering other generation sources than renewables. They indicate the scarcity only by the residual load. This approach does not display the interdependences of the market players (e.g. renewables and storage). Therefore, Fraunhofer IEE, 2018 and this thesis considers other suppliers as well and focus on the impact of changing parameters on the scarcity instead of the absolute values.

The chosen generation mix with its missing secured capacity results in a high level of scarcity in the first experiment. In the second one, it gives the backup technology a dominant market position in the hours, which are scarcity hours in the first experiment. Due to their configuration in AMIRIS, the gas turbines keep bidding their marginal costs, which results in a lacking cost recovery. The missing exercise of market power is considered as unrealistic in this case.

The acceptance of an extensive exercise of the market power is an unrealistic extreme case as well. The gas turbines would increase their bids to cover their costs and exploit their dominant position as shown in the markup analysis. As other market players (e.g. battery storage) aim to capitalize on the higher prices as well, a reciprocal effect that a higher bid leads to a lower awarded quantity is observed. This observed market dynamic is bounded by the limited available energy in this simulation setup. A lower level of missing secured capacity would decrease the dominance of the backup technologies and show how the price increase would be limited by other market players. An appropriate level of missing capacity for this simulation setup needs to be determined by a sensitivity analysis before the simulation. A more realistic representation of the market power by the backup technology and the resulting cost recovery is subject to further simulations.

Fraunhofer IEE, 2018 and Huneke et al., 2017 see the need for additional backup capacity as well. For instance, Fraunhofer IEE, 2018 recommends to install 30 GW gas turbines too, but bases the recommendation on a scenario with a higher renewable share and more sectoral coupling.

Further simplifications are made to keep the scope of the thesis feasible. The most influential ones and their impact on the final outcome are explained in the following.

First of all, a mix of backup technologies could be created which is tailored to the challenges of the scarcity. In the analysis, only one type of backup technologies is used due to feasibility reasons. This impacts the simulation and the calculation of the missing money. For the second experiment, a mix of technologies could be implemented instead of only one backup technology. As only one kind of storage and only conventional power plants are able to provide secured capacity in AMIRIS, the means are limited. At the same time, the reasonable differentiation between eligible and non-eligible power plant for financial support is difficult. Therefore, the focus of the costs analysis is set on the entire portfolio of the gas turbines. This includes 7 GW of already installed gas turbines and 30 GW of additional gas turbines. This simplified scope allows a direct allocation of the impact on the cost recovery for the different scenarios. Different criteria can be used for the selection of units which are considered as backup technologies and are eligible for financial support (e.g. targeted or market-wide). The analysis could be refined by a stringently selected mix of backup units based on prequalification criteria.

Second, Huneke et al., 2017 adapts not only the renewable output according to the weather years, but the demand as well. This results in an average load of 73 GW for the Dunkelflaute for the extreme weather year of its analysis. Compared to that, the average residual load of this simulation is 34 GW[25]for the extreme weather year of this analysis 2010. The simulation could be refined by the usage of a weather dependent demand curve.

[25] As the residual load does not fall below 40 GW during these two weeks, a significant level of electric heating and other continuously running electrical devices must be used by (Huneke et al., 2017).

The technology analysis and simulation are based on costs forecasts for fuel price, CO_2 price and other costs factors. These are subject to uncertainty. The impact of most pivotal factors is assessed by sensitivities. The uncertainty for the costs of excess energy which is transformed into synthetic gas by power-to-gas applications has a more principle character. It is not clear how the renewable operators will handle their excess energy in the future. In the simulation, the renewable agents receive a market premium to ensure that they trade their excess energy on the market to some extent. This is a simplification, as it is unlikely that they still receive a market premium like nowadays by 2040/2050. At the same time, renewable operators would curtail their energy, if they lose money by offering it on the wholesale market. A new way of trading excess energy needs to be defined. As proposed in the technology analysis, bilateral contracts are one option.

The determination of the costs for excess energy is also key for the transfer of the market income of the fossil gas application to the power-to-methane facilities. It matches the different cost structure and bidding patterns of both technologies with the same income. The income of the backup technologies tends to be similar, as both strive for high prices. Additionally, it can be assumed that the extensive storage facilities of power-to-methane do not limit continuous bidding during hours with high prices. The bidding restraints, which are observed for battery storage to maximize its profit, are not allowed for backup storages. In times of scarcity, power-to-methane is obliged to bid in a way to minimize the system costs. The switch from a profit-maximizing to a system costs-minimizing strategy at scarcity moments is difficult to implement in the model. Penalties for non-bidding during scarcity moments could be used. This design challenge is subject to further research.

Other costs factors are simplified as well. For the calculation of the deficit of the backup technologies, only the fixed and variable costs are not considered. Common costs positions of an investment plan, such as internal rate of return, are not considered. Additionally, no risk premiums are included neither. It is not clear how high are the risk premiums for investment in backup technologies under these conditions or whether the investors are willing to take these risks at all. The risk premiums under these investment conditions are a key factor for the investment into backup technologies and need to be investigated further.

12.4 Pricing the Contribution on Security of Supply

The skepticism about the price signals of the EoM to incite investment into backup technologies is reinforced by the analysis. Therefore, interventions to stimulate investments and maintain the security of supply are evaluated. The analysis focus on centrally organized instruments by the system operator. Alternative measures which reinforce the EoM without a radical intervention are not considered in the scope of the thesis. Those can be, for example, opening the balancing market for new flexibility providers. It is assumed that measures like this would stimulate flexibility to some extent but not incite capital-intensive investments. In the future energy system like the simulated one, a bulk of flexibility and therefore investments are needed. The underlying question is to which extent the accompanying measures for the EoM are able to incite flexibility and when a comprehensive intervention is needed.

Looking at this future point in time, the question occurs which intervention is best suited to ensure security of supply in a cost-efficient way. It is answered by the MCDA about capacity mechanisms. The analysis is based on mainly qualitative literature and only limited empirical findings. A more extensive involvement of empirical findings of already existing capacity mechanisms would improve the quality of the analysis. At the same time, the structural differences of the German and the other energy system need to be taken into account to transfer the effects of the capacity mechanism. An extensive study like this was not possible due to time constraints.

For the MCDA in general, the translation of qualitative findings into a quantitative rating and the weighting of the criteria run the risk of bias and the legitimization of own preferences. For the translation of the findings, a transparent reasoning mitigates the risk. For the weighting of the criteria, reference values add neutrality. In this case, the cost structure of the renewable subsidy is used as a rough indicator. The similar pattern of both interventions legitimates this comparison in principle, but its differences such as the subsidy budget need to be considered. As soon as an empirical cost evaluation about an existing capacity mechanism is published, the weighing shall be updated with this more matching reference.

The general functioning of the selected capacity mechanism, the capacity subscription, on the security of supply aim to be demonstrated exemplarily in the final part of the analysis. The comprehensive design of capacity subscriptions and forecasts for self-rationing cannot be examined due to time constraints. The main drawbacks of the simplified calculation are explained in the following. The ex-post analysis gives the suppliers and users of the capacity subscription the chance to align their bids exactly to their costs and the existing scarcity moments. The suppliers calculate the payments based on their costs deficit. The users base their request on the tradeoff considering the demand shedding costs for the load peaks and the payments for the capacity subscriptions. This unrealistic case of perfect knowledge is usually replaced by a sophisticated allocation mechanism which considers the costs of several years, forecasts for the requested capacity subscription, risk premiums and other transaction costs. The costs of energy supply for the consumer in case of an EoM with and without a capacity market by (Bhagwat et al., 2017) give an indication of a more realistic costs difference for a market-based and regulatory approach.

The calculation of markups is simplified as well. No dynamics due to the competitive environment or changing markups according to the price distribution are considered. Furthermore, the operators do not possess perfect information about the future scarcities. If the price is lower than their bid but higher than their marginal costs, they reduce their profit by their misjudgment. Both simplified calculations make the comparison of total costs for the consumer vulnerable.

Additionally, the cost recovery cannot be used as the only requirement for triggering investments. Analysis about the market dynamics, the competitive environment or the level of scarcity prices which trigger investments in certain technologies would underpin the analysis.

Last but not least, two more general aspects need to be considered for maintaining the security of supply. On the one hand, the consumers of our generation are not used to pay extra for the service of security of supply or handling the consequences of scarcity. Both outcomes might be overwhelming for them. Therefore, they need to be prepared by information campaigns and equipped with tools to handle it (e.g. like smart meters for demand response) by their retailer or the regulator.

On the other hand, it is a fundamental decision whether the market or the regulator is the most capable party to decide on backup investments and handle the investment risk. A sound judgment is needed to decide on the degree of intervention by the regulator and to design a suitable intervention. This key issue cannot be addressed solely by this thesis but its investigations about the impact of the weather on a renewable dominated energy system and possible measures to maintain security of supply contribute to the discussion.

13 Conclusion

By increasing the share of photovoltaic and wind on the generation mix, the energy supply becomes more weather dependent. To maintain the security of supply, the volatile power output by the renewables needs to be compensated by other sources. These flexibility options need to handle diverse incidents of scarcity ranging from single peaks of uncovered load to longer scarcity periods. Their intensity depends on the weather conditions. The analysis of two contrary weather years gives a range for the need of additional flexibility.

More than one-third of the high uncovered load peaks are surrounded by a scarcity period of almost a day and longer. This situation is especially prevalent for the Dunkelflaute. In the reference scenario of the thesis, the maximum peak occurs in a period of almost three days of scarcity. These scarcity incidents cannot be covered by short-term flexibility solely. The extreme peaks and the long duration of uncovered load are asking for additional investment in backup technologies. The increasing share of fluctuating renewables and the yearly changing request for backup energy can be well addressed by the installation of a gas turbine supplied with fossil gas, which is replacement by synaptic gas from power-to-methane after a while.

If no scarcity and no scarcity prices are accepted in the future power system, the backup technologies cannot recover their fixed costs. The business case is further deteriorated by the risks coming from unpredictable parameters. For instance, the margin is reduced by 83 percent comparing the most extreme and the mildest weather year and it is four times lower by battery storage. The pricing of the provision of backup capacity lowers these risks and contributes to the maintenance of security of supply.

Capacity subscriptions do not only ensure the cost recovery of backup capacity but activate further efficiency potentials. The consumers can decide whether they contribute to the security of supply by reducing their load or pay for the backup capacities. In the shown example with industrial consumers, the mix of the activation of demand shedding and capacity subscriptions lead to the lowest total costs for the consumers compared to the alternative scenarios of accepting scarcity prices or markups.

To address the technological and economic perspective of the research question and provide the full picture, some shortcuts and simplifications need to be made. Aspects such as the sequence of weather years, the dominant market position of backup technologies and the interaction of more than one storage operator on the market are subject of further research.

All in all, the interplay between the suitable technological choices, the institutional course setting and the involvement of innovative flexibility options prepare the ground for a secure, affordable and sustainable energy transition.

14 Reflection

Even though I enjoy the gained insight into the future challenges of the energy transition, the greatest value for me are the lessons on the way of creating them. The topic of the thesis allowed me to apply the variety of knowledge and tools which I acquired during the master program to tackle complex socio-technical challenges. In the following, I aim to reflect on the methodology, especially the agent-based model AMIRIS, the process and the application of the content from the master program.

The main methodology, the agent-based model AMIRIS, is accompanied by literature analyses and the further processing of the model output by calculations. For the literature analyses, the MCDA was a useful method to structure and evaluate the findings of the capacity mechanisms. The main benefit of the MCDA was that qualitative findings could be transferred into quantitative indicators, weighted according to their importance and based on that selected.

The transfer from qualitative to quantitative findings was also a key element for the evaluation of the backup technologies. A streamlined bundling of all relevant factors in the cost comparison enabled a selection based on the costs without the need of reconsideration of qualitative findings. The two-stage procedure of eligible technology screening and the following evaluation narrowed the scope of technologies. In the hindsight, the initial screening of technologies could be shortened. Starting with the full range of flexibility providers, the preselection with an established set of criteria confirmed the commonly known gas applications as the main backup technologies. A decision of not doing everything from the scratch and basing the starting point on some preliminary work would have given me more freedom and time for the investigations which create new insights (e.g. about market dynamics).

I had the great chance to base my work on the agent-based model AMIRIS and the provided data by DLR. My thesis internship at DLR just started before a new launch of the model, in which the energy exchange was newly structured and the storage agent implemented. Both aspects were extremely useful for my investigation. The user-friendliness of the model allowed me to create my own scenarios easily. The only drawback was that some parts of the previous documentation, validation, and verification were not valid for this version anymore. This was compensated by the help of the employees at DLR.

One aspect which was more time consuming than I expected was to understand and question the behavior of the storage. Its arbitrary strategy results on bids which are sometimes not straightforward to understand. For instance, the fact that the storage does not use all positive and negative extreme prices. This understanding was key to differentiate which bids are a result of the specific model configuration or a generalizable finding. Getting to know the various forms of the storage gave me an idea of how challenging the creation and verification of the storage agent must have been, which was done by an employee at DLR.

The output of the model was given in form of excel sheets. This allowed me to create a standard spreadsheet which evaluated the key indicators automatically, as soon as I transferred it to the output sheet. This facilitated the evaluation in an easy and systematic way. A minor hint for future new users is to name the output files in a consistent way to find the needed one after several runs.

Another main benefit of AMIRIS is the short computing time of a few minutes. This gave me the freedom to test the outcome of different configurations in a short time.

In context of the configuration of the input data, two lessons learnt are made. First, the input data needs to be consistent. A mix and match approach of not fitting data from several sources can lead to unintended model artefacts, which do not reflect reality. One example is the fit of the renewable time series and their installed capacity to create the intended share of renewables. It was helpful to base my scenario specification on an already existing one which used the same time series provided by the DLR as well.

Another insights, which I realized too late to use it by myself, is that the sensitivity analysis could have been used before the experiments to check the input data for its impact on the model outcome (e.g. capacity gap) and to adjust it and not after the experiment to see how the results change in context of adapted parameters.

For the presentation of the results, it was key not to overload the graphs with not relevant information for its intended statement and differentiate between the outcomes which are just a consequence of the input data (the before called model artefacts) and generalizable findings.

In the hindsight, less time could have been invested in the qualitative part to have more freedom to exhaust the possibilities of the model. Those range from smaller aspects (e.g. implementation of forecasting errors) to modifications of the model (e.g. implementation of capacity mechanisms). Other modifications are extremely interesting as well (e.g. involvement of investment decisions) but it would have been impossible with the available time and prior knowledge to implement it.

Looking at the process, the investigations of that broad topic was extremely interesting. Frequent meetings with my supervisors from DLR helped me to progress and generate new insights every week. At the same time, it was a challenge of not to lose focus considering the range of linked aspect of the security of supply. The main risk was by trying to do everything to do nothing properly. For instance, the indicative calculations in the end of the thesis are a borderline case of it.

Without the prior knowledge of the energy economics, energy modeling, energy optimization, network and institutional economics courses, the handling of the scope of the thesis would have been hardly feasible. The course “Electricity and Gas: Market Design and Policy Instruments” provided me with a knowledge base about energy economics and regulation. The course “Desing of Integrated Energy Systems” showed me that working with models is not only about understanding the coding or its manual but how to utilize them for a special aim, make decisions and create robust findings.

The institutional economics course equipped me with knowledge about market interventions. Even though I did not apply it directly in my research, the Institutional Analysis and Development Framework by Elinor Ostrom was a help to structure and explain the different capacity mechanisms. The tools learned in “Engineering Optimization and Integrating Renewables in Electricity Markets” enabled a simplified optimization for the self-rationing of capacity subscriptions. The game theory content of “Design in Networked Systems” helped to understand the complexity of interdependent bidding strategy of storages.

Last but not least, it took a while for me to understand the possibilities of agent-based models. If I have had this insight at the beginning of my study, my course selection would have focused more on it. As a more competent user of AMIRIS, I could have seized its potential in a better way. Fortunately, it is never too late to learn and I am happy to make this experience at the end of my studies.

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Appendix

A. Residual Load Curve

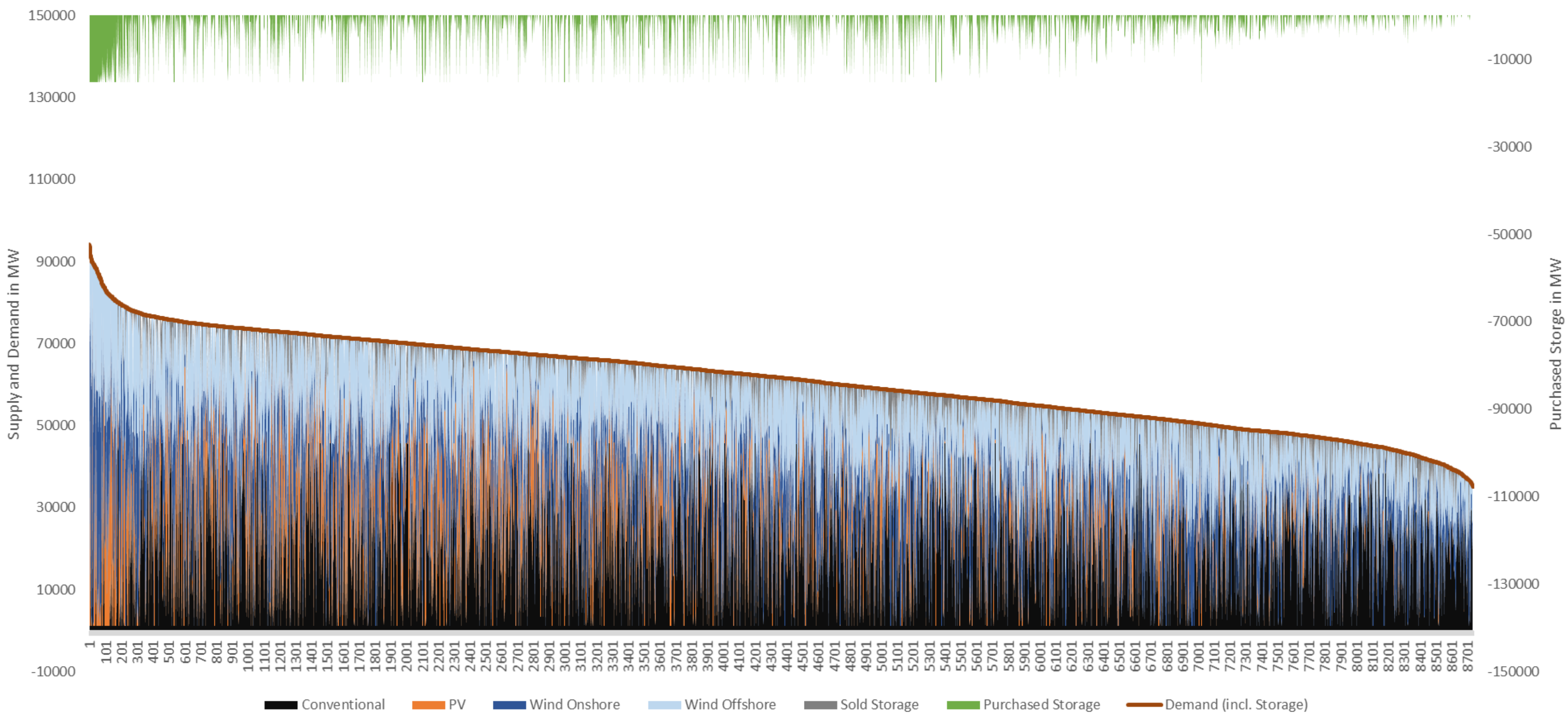

Figure 80: Load duration curve for weather year 2010 with 15 GW storage and basic renewable share

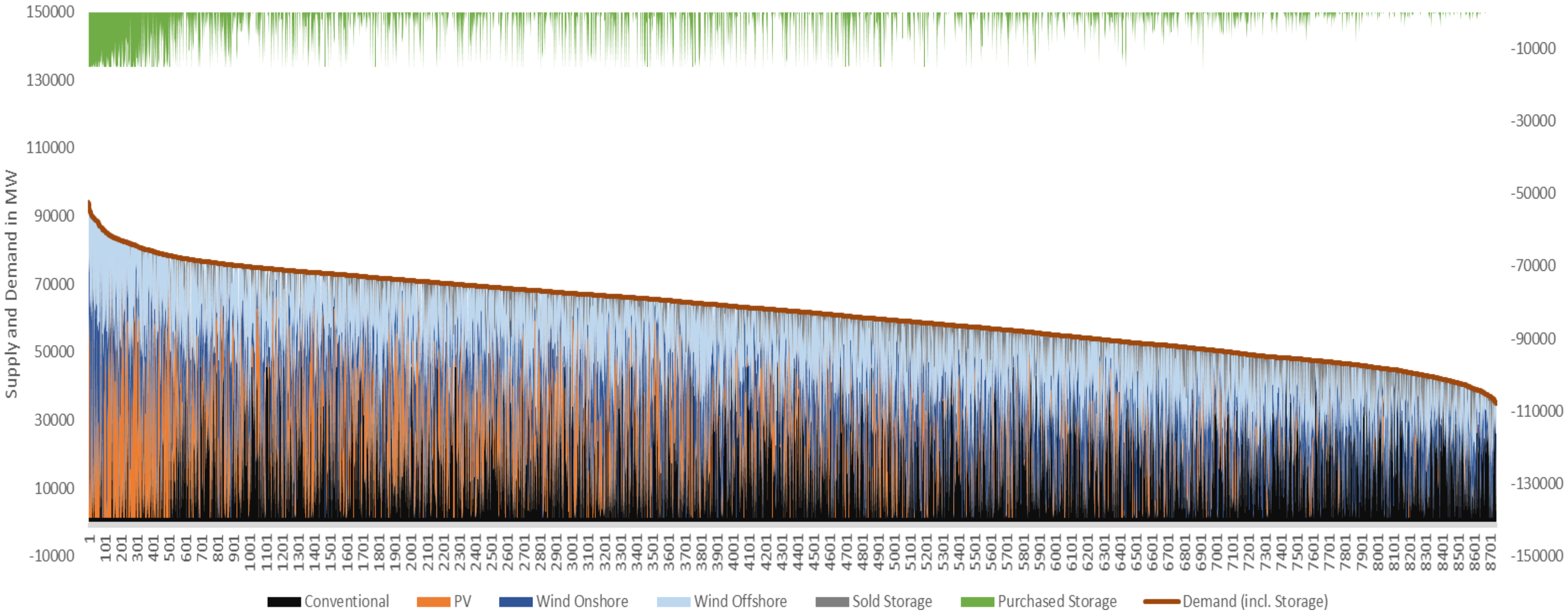

Figure 81: Load duration curve for the weather year 2010 with 15 GW battery storage and 50 GW PV +

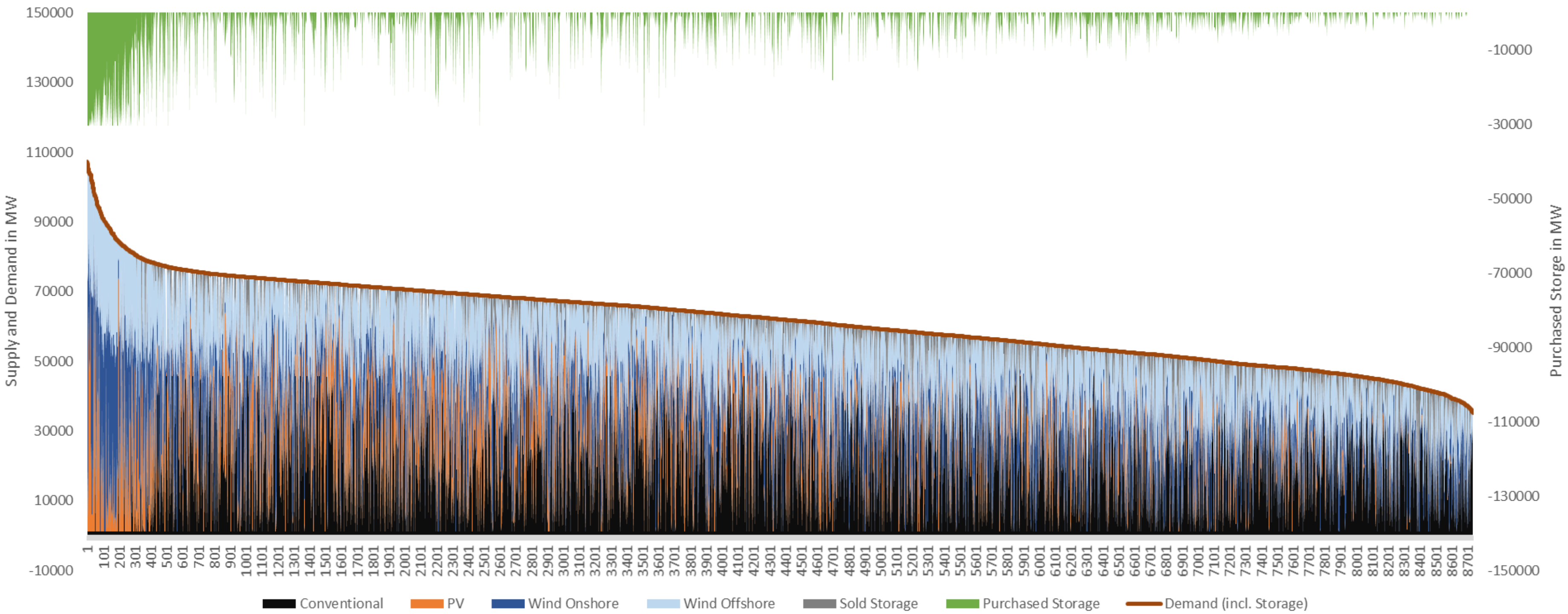

Figure 82: Load duration curve for 2010 with 30 GW battery storage and basic renewable share

B. Residual Load Duration Curve
(Hours with highest residual load)

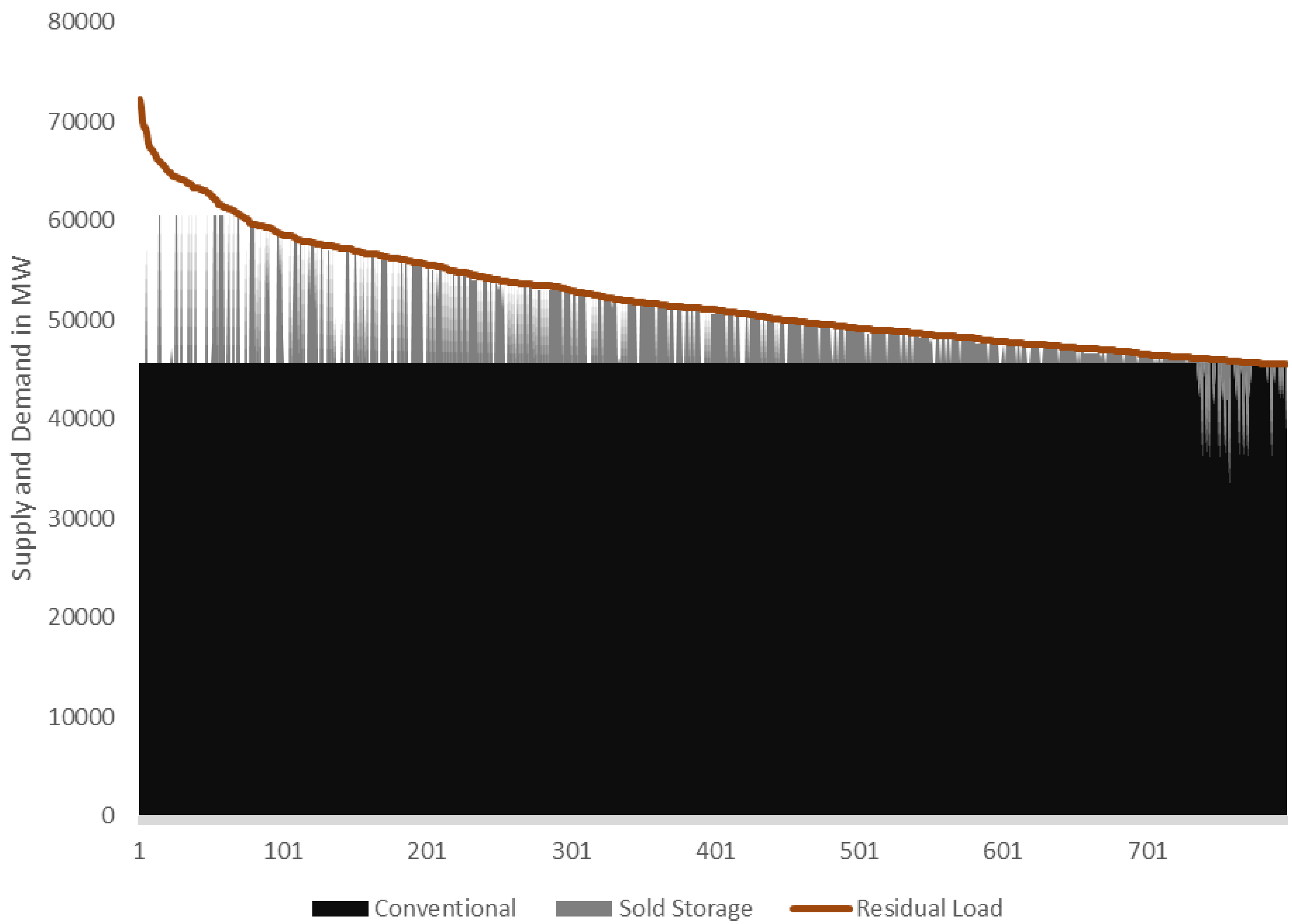

Figure 83: Residual load duration curve for reference scenario

C. Yearly Photovoltaic Generation Pattern

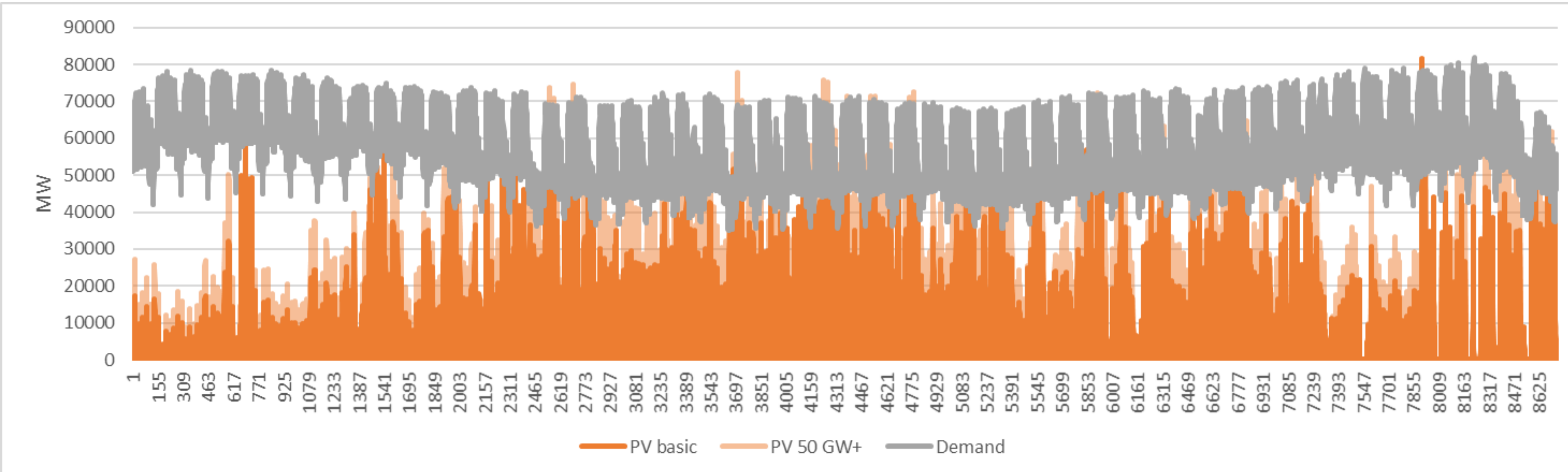

Figure 84: Yearly generation pattern photovoltaic