The Impact of Weather Conditions and Availability of Batteries on the Cost Recovery of Gas Turbines as Backup Capacity in a Renewable Dominated System

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Abstract

With an increasing the share of photovoltaic and wind in the generation mix, the power supply reduces its CO2 emission and becomes more weather dependent. Their volatile power output asks for a compensation by backup technologies. Gas turbines and other backup technologies need to handle diverse incidents of scarcity ranging from single peaks of uncovered load to longer scarcity periods. The analysis of two contrary weather years by the agent-based model AMIRIS shows the range of the scarcity incidents and determines the cost recovery of back technologies depending on weather conditions and the availability of batteries. Batteries can mitigate the scarcity only to some extent due to their technical limitations. At the same time, they diminish the investment basis for capital intense backup technologies. The emergence of batteries leads to a four times lower margin of the backup capacity. Mild weather conditions with a high renewables output divide the margin in half compared to extreme weather conditions. Despite the volatile backup energy request and income basis for the different scenarios, a similar level of backup capacity needs to be installed to cover the constantly high maximum scarcity peak. As investments are unlikely considering the lacking cost recovery and volatile revenue streams, additional revenue streams are needed to guarantee a sufficient level of secured capacity for maintaining the security of supply.

Keywords: Security of supply, weather, batteries, backup capacity, flexibility

1. Introduction

Motivation

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 CO2 emissions and becomes more sustainable. At the same time, the challenge of ensuring the security of supply reaches another level with a more weather dependent generation mix.

Especially winter days with fog, still air and a high power demand (the so-called Dunkelflaute) are a stress test for the new power system. For instance, on the 24. January 2017 the overall electricity demand of 83 gigawatts (GW) could be only covered by max. 3 GW renewables (Agora, 2018). Nowadays, shortcomings like this are bridged by conventional power plants and cross-border imports. As the increasing share of photovoltaic and wind energy replaces conventional power plants in the market, technologies which are specially implemented for the scarcity moments (the so-called backup technologies) are needed to maintain the security of supply.

The cost recovery determines the likeness of investments in backup capacity. As last dispatched power plant, backup technologies need scarcity prices to cover their fixed cost. In a renewable dominated power system, the frequency of scarcity prices depends mainly on the energy supply by weather-dependent renewables and the availability of short-term flexibility providers. The impact of the weather conditions and the short-term flexibility provision on the cost recovery is analyzed for the case of two contrary extreme weather years and batteries. The required backup capacity to cover the scarcity in a renewable dominated energy system and its income is determined with the help of the agent-based model AMIRIS. The model and its scenarios are explained in the chapters 2 and 3. The results are presented, tested with a sensitivity analysis and discussed in chapter 4, 5 and 6.

Literature Review

The weather does not only differ from month to month but from year to year. The increasing weather dependence forces backup technologies to readjust their business case to a time span of several years and a high level of uncertainty. The weather-dependent backup request is a subject of several publications.

(Becker, 2018; Fraunhofer IEE, 2018; Huneke, Perez Linkenheil, & Niggemeier, 2017) demonstrate the correlation of weather and renewable output. Whereas (Becker, 2018) focuses in the coincidence of the energy output for different renewable technologies, (Fraunhofer IEE, 2018; Huneke et al., 2017) set the renewables in context of a future energy system and presented the resulting scarcity moments.

(Becker, 2018) highlights that the yearly occurrence of a consecutive renewable energy shortage over two days can be reduced from 23 times to two times by the switch from a sole supply by onshore wind energy to a mix of onshore, offshore and photovoltaic.

(Huneke et al., 2017) identifies the weather year 2016 as the mildest and 2006 as the most extreme one. Two weeks at the end of January show the highest scarcity. With a generation mix of 69 percent renewables, the average residual load of these weeks is 72.8 GW for the weather year 2006. The uncovered load of this period ranges from 4.47 TWh for 2016 to 22.88 TWh for 2006.

(Fraunhofer IEE, 2018) ranks the weather year 2007 as the mildest and 2010 as the most extreme one. Similar to (Huneke et al., 2017), the last three weeks of January are the stress test for the energy system. The different input parameters and indicators for the output impede a comparison of the results. A high degree of sectoral coupling and a generation mix with 95 percent renewables result in a maximum gap between demand and supply of 30 GW for the weather year 2010. The uncovered load ranges from 1 TWh for 2007 to 3.9 TWh for 2010.

(Fraunhofer IEE, 2018) shows that different forms of flexibility help to reduce the backup capacity need to low level. The emergence of batteries plays a special role in this context. The literature differentiates

between two main use cases. They can be either used to minimize the system cost (Sioshansi, Denholm, Jenkin, & Weiss, 2009; Zapf, 2017) or maximize the profit of its owner (Conejero, Díaz, & Gomez, 2018; He et al., 2016; Majidi, Nojavan, & Zare, 2017; Simshauser, 2018). The latter is based on an arbitrary strategy for which the battery is modeled as a monopoly of short-term flexibility. The more realistic case of interdependent arbitrary strategies in a competitive environment for storages is more difficult to model and requires elements of game theory (Wang, Ai, Tan, Yan, & Shuting, 2015).

The publications indicate a range of backup requests and different ways of utilizing batteries but do not merge this information into the changing cost recovery conditions of backup technologies. By using 2007 and 2010 as the two contrary extreme weather years like (Fraunhofer IEE, 2018) and a profit-maximizing monopolistic battery operator, the cost recovery is analyzed in the following.

2. Methodology

Different parameters of demand and supply with a high temporal resolution need to be merged to evaluate the scarcity incidents which shall be addressed by the backup capacity. This is done with the help of an energy dispatch 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 AMIRIS by the German Aerospace Centre (DLR).

As illustrated in figure 1, 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.

Within the simulation of AMIRIS, some actors are entitled to optimize themselves by making decisions (see figure 2). For instance, the storage adapts its bidding based on

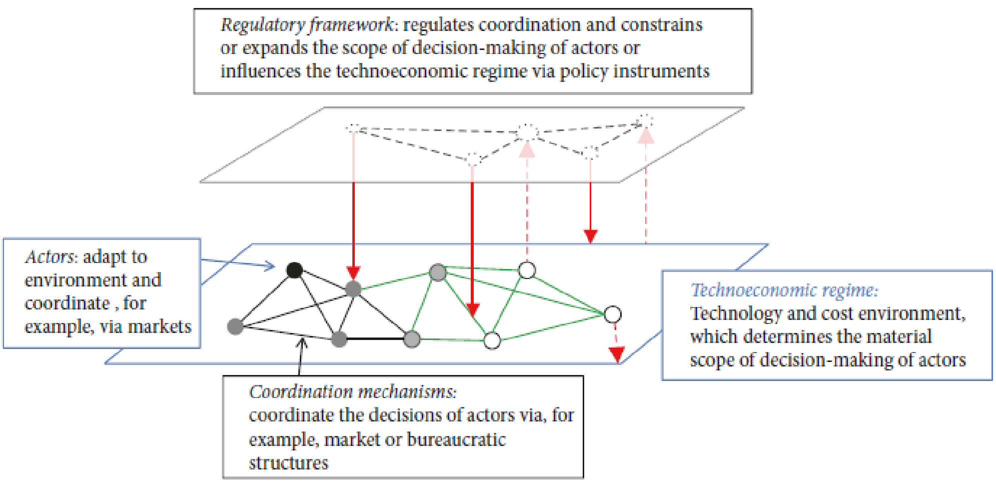

Figure 1: Conceptual approach by AMIRIS, source: (Deissenroth et al., 2017)

information about the future dispatch to maximize its profit. It capitalizes on the price spread by charging during low prices and discharging during high prices. The level of foresight can be defined as one configuration variable of the storage (Schimeczek, Deissenroth, Fleischer, & Reeg, 2018).

The installed capacity of the generation mix is determined exogenously. It is derived from common literature and evaluations by the linear optimization model ReMix by DLR, which use the same database.

The actors are differentiated by their technology. Every generator is linked to one trader. For the controllable generators, the trader creates the bid for the energy exchange based on the installed capacity, the variable cost, 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 fluctuating 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 renewable generators are assigned to a technology specific and fixed market premium. 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, Klein, Nienhaus, & Reeg, 2017).

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. The energy exchange creates the merit order based on the bids by the traders, dispatches it with 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 negative minute reserve and the system operator are not considered in this investigation.

The model is verified and validated by (Klein, 2018; Pelka, 2018; Schimeczek et al., 2018).

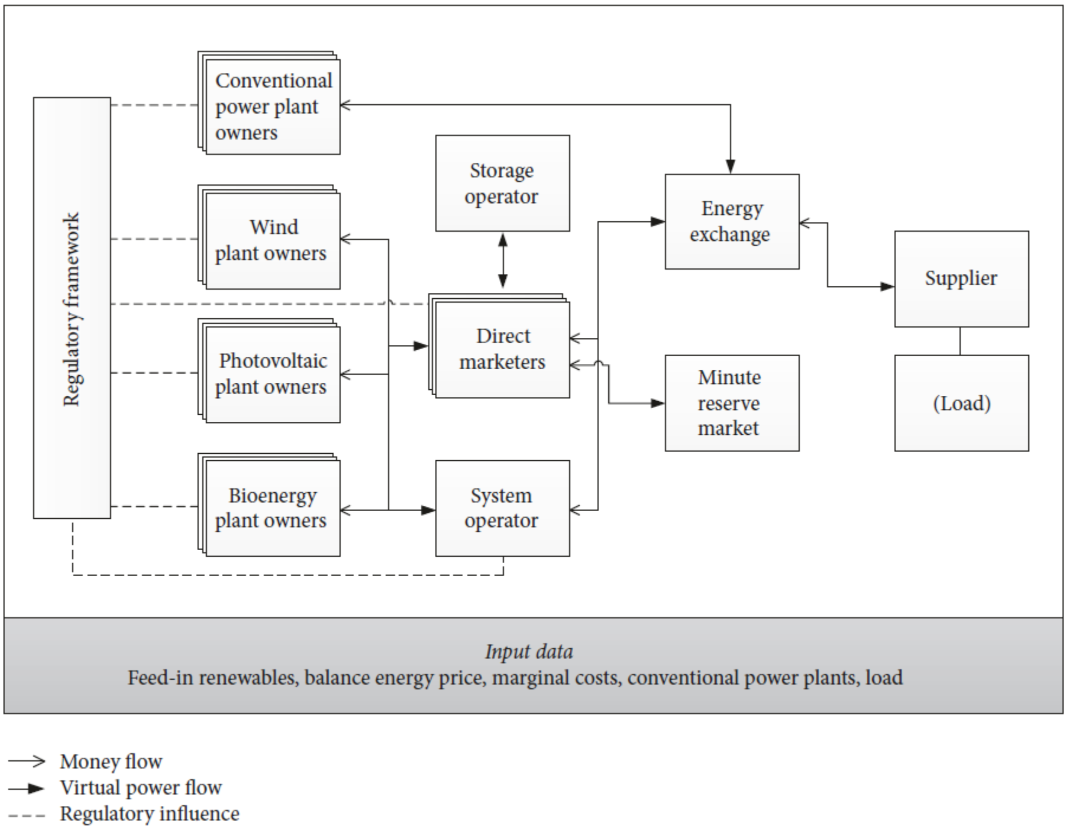

Figure 2: The AMIRIS model, source: (Deissenroth et al., 2017)

3. Scenarios

Three scenarios aim to be simulated to test the impact of the weather and the batteries. The reference scenario consists of the extreme weather year with little renewable output and a certain level of batteries. The two alternative scenarios enable a comparison with the mild weather year and the same level of batteries (“scenario mild weather”) or no batteries and the same weather conditions like in the reference scenario (“scenario no batteries”).

The impact on the cost recovery is examined by a two-stage procedure. First, the scarcity incidents which the backup technology and partly the battery aim to cover are analyzed. Hereby, the different character of scarcity is documented with the help of three indicators. Those are the maximum scarcity peak, the uncovered load over the entire year and the uncovered load during the longest scarcity period. The maximum scarcity peak indicates the needed backup capacity and the yearly uncovered load the requested backup energy. The uncovered load of the longest scarcity period stresses the potential of batteries to bridge scarcity.

In the second stage, a gas turbine is implemented as backup technology. The income derived from the simulation is matched with their total cost for the installed capacity and the requested backup energy. The costs are based on (Buttler, Hentschel, Kahlert, & Angerer, 2015; Cebulla, 2017; Pfluger et al., 2017).

The underlying data is used from (Cebulla, 2017) who created a renewable dominated energy system with a range of different storage technologies. Two modifications of the scenario with a high CO2 price of 75 EUR/t are made. First of all, the renewable share in the simulation aims to be similar to the renewable target of the German government for 2040 (BMWi, 2015). To raise the share of 61 percent by (Cebulla, 2017) to 66 percent of the yearly consumption, 20 GW installed capacity for wind onshore are added. By this update, the installed capacity for wind onshore shows the same level as in the long-term forecast of the Federal Ministry for Economic Affairs and Energy (Pfluger et al., 2017).

The second modification is about the creation of investment restraints. In the scenario by (Cebulla, 2017), sufficient investments in generation and storage are made to cover the demand for every hour of the year. This includes also investments in storage technologies with an uncertain business case like power-to-hydrogen and compressed air storages. Assuming investment restraints for these technologies due to an uncertain cost recovery, only 15 GW li-ion batteries are considered. A limited foresight of one day is assumed for the battery operator. The remaining 23 GW storage capacity is excluded as a capacity gap.

The level of the capacity gap and foresight for the battery storage are likely to influence the simulation outcome significantly. Their impact is tested in a sensitivity analysis.

4. Results

Scarcity Incidents addressed by Backup Capacity

With 26 GW, 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 short-term storage.

In contrast, the weather conditions and level of short-term storage influence the amount of missing energy. The storage is able to divide the yearly missing energy in 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.

Looking at the frequency of scarcity peaks per year, the weather year 2010 shows 36 percent more peaks in the category 10 to 20 GW. The correlation between scarcity peaks and longer scarcity periods reinforces the severity of scarcity for the weather year 2010. 35 percent (2010) and 25 percent (2007) of the extreme peaks can be found in a scarcity period longer than 20 hours (see figure 3 and 4).

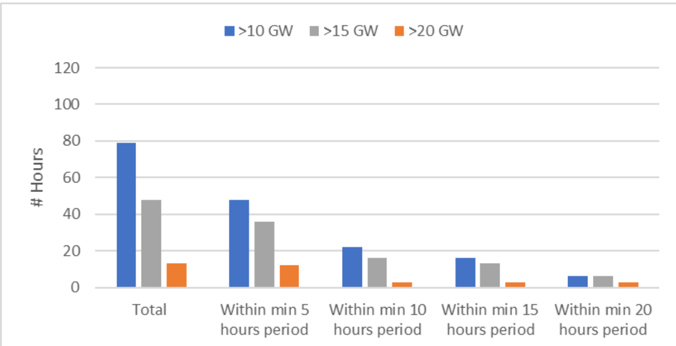

Figure 3: Correlation of hours with uncovered load peaks and consecutive hours of the uncovered load for 2007

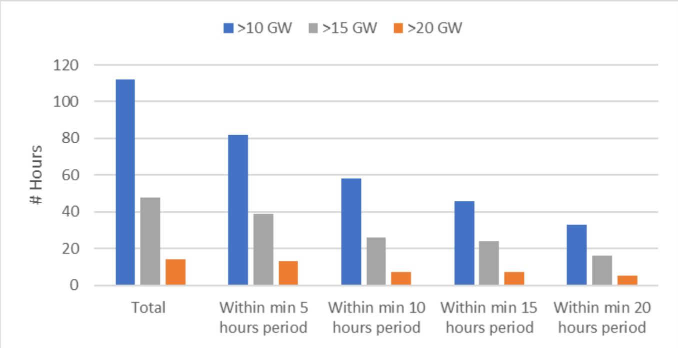

Figure 4: Correlation hours with uncovered load peaks and consecutive hours of the uncovered load for 2010

The severity of the scarcity become more explicit for the investigation of the longest scarcity period of each year. The most extreme period can be found in the reference scenario lasting for almost three days. The missing energy is ca. three times higher for the extreme weather year than for the mild one. This leads to a condensed accumulation of scarcity moments which cannot be addressed by the battery solely. Due to the limited eligible moments to charge, the contribution of the battery to cover the missing energy is ca. one-tenth less than at 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 by batteries. The maximum scarcity 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 batteries.

Cost Recovery of Gas Turbines

Considering the maximum scarcity peak, a technology typical non-availability rate and technical efficiency, additional gas turbine capacity is implemented to bridge the scarcity. The income and total cost are merged for the entire installed capacity of the technology.

The decrease of missing energy in the case of more storage or milder weather presented in the first step gives already an indication for the lower full load hours of the backup technology and its reduced margin. The evaluation of the second stop demonstrates that the backup technology is not able to cover its total cost in any scenario. Although the level of missing money is dependent on the exogenously determined generation mix and therefore susceptible, it needs to be considered that the backup technologies do not even recover their cost under extreme scarcity conditions.

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 step 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.

5. Sensitivity Analysis

It can be presumed that the level of the capacity gap influences the scarcity and that longer foresight and thereby more information about the future dispatch support the storage to maximize its profit and to weaken the cost recovery of the backup technology. Both assumptions are tested by the sensitivity analysis.

A longer foresight of one week leads to an 11 percent higher income for the battery. By knowing with a longer foresight when attractive hours are about to come, it is able to use more positive extreme prices. Thereby, it decreases the uncovered load per year by 20 percent.

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 (see figure 5). It gives the impression that within the foresight period no more high prices exist which could be addressed by additional stored energy. The eligibility of the sequence of prices for the frequent charging and discharging of a battery needs to be evaluated further.

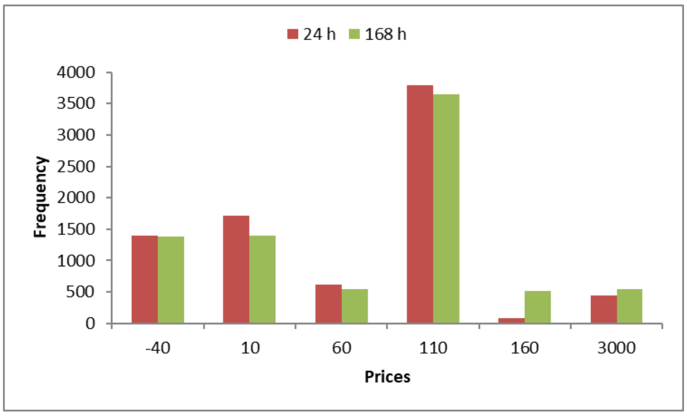

Figure 5: Distribution of prices for storage utilization with different foresights

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

The optimized bidding with the help of the longer foresight decreases the margin of the backup technology by 25 percent. Consequently, a longer foresight does not support a more system friendly usage of battery beyond a certain level due to its technical limitations, but it weakens the security of supply indirectly by lowering the margin of the backup technologies.

By halving the capacity gap, the additional capacity is directly translated into a reduction of the maximum scarcity peak. This effect can be endorsed for the other hours of scarcity. The uncovered load per year only accounts for 6 percent of the previous value. For the longest scarcity period, it is 12 percent. The level of the capacity gap is a sensitive parameter for the analysis. Especially the frequent scarcity in hours with a little missing capacity could be covered easily.

6. Discussion

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 excluded investments 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 consider 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) discusses the gap between optimal and real market outcomes. Simulations and optimizations have advantages and drawbacks as 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.

Furthermore, the presented scarcity indicators identify the most apparent scarcity moments but do not provide a comprehensive 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 changes 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.

The simulated participation of short-term 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. Three distinctions need to be made assessing the transferability of the simulation results on the real impact of batteries on the security of supply.

First of all, the ownership and operation of batteries are likely to be spread over a heterogeneous set of actors in the future. 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 (Wang et al., 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, the bidding of the exact amount of energy to use the high price without lowering them is unlikely. As the price is likely to be lowered anyway, the storages create profit by selling their stored power instead of holding the price artificially high. 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.

Furthermore, 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.

All in all, the skepticism about the price signals of the EoM to incite investment into capital intense backup technologies is reinforced by the analysis. Therefore, interventions to stimulate investments and maintain the security of supply need to be taken into consideration.

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.

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. In the reference scenario, 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 maximum scarcity peak sets the benchmark for the dimension of backup capacity. The combination of similar maximum peaks for every scenario and the divergent levels of requested energy by the backup technologies are already a negative indicator of its cost recovery. This is proven by the simulation with the backup technology. Even though the input parameters create an unrealistic extreme case of scarcity, the backup technology cannot recover its total cost. 8.5 percent of the hours per year show scarcity prices of 3 000 EUR/MWh. It is unlikely that a regulator would expose the consumers to such a great scarcity without intervening.

Referring to the scenario with the highest likeness of cost recovery, the one without storage and extreme weather, the implementation of short-term storage lowers the margin four times and additionally, mild weather conditions lower it two times further. It becomes clear that not only the lacking cost recovery restrains investment into backup capacity but also the risk connected to the volatile level of deficit. The pricing of the provision of backup capacity by capacity mechanism lowers these risks and contributes to the maintenance of security of supply.

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