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Market based decarbonization and the interaction with reliability policies

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Market based decarbonization and the interaction with reliability policies

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Market based decarbonization and the interaction with reliability policies

Georg Thomaßen^a and Thomas Bruckner

– Preprint –

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Abstract

This paper investigates market-based decarbonization, driven by carbon pricing, and under different regulatory settings. These consist of a conventional energy-only market (EOM), an EOM with operating reserve demand curve (ORDC) and a capacity market (CM).

We find that contrary to previous research findings, all markets produce conclusive market outcomes in all stages of decarbonization, as flexible technologies create market signals that ensure the economic viability of renewables. This is relevant for systems that rely on carbon pricing, but also for those relying on out-of-the-market measures to deploy renewables, as it implies that markets can be deregulated again later if carbon prices are sufficiently high.

All three regulatory scenarios further achieve close-to-optimal market outcomes, if they are calibrated well. The outcome in CMs, however, is especially prone to suboptimal configurations, relying on several design parameters, which are commonly deducted from weather data and system projections. Varying only one of these parameters induced large changes in the observed generation mix. ORDCs provided more stable results, even if the input parameters differed strongly from optimal values. We therefore recommend to rely on ORDCs to maintain resource adequacy, as they appear to produce lower costs and interfere less with the general market dynamics than CMs.

1 Introduction

Power systems around the world are currently undergoing a transformational process to lower the carbon intensity of their system, shifting away from fossil fuels and towards renewable energies. Wind power and solar photovoltaics (PV) are the dominant sources, because of their low costs. This transformation marks a paradigm change, which goes beyond simply replacing carbon intensive fuels with climate neutral ones. Variable renewable electricity (VRE) generators are “fueled” by the sun and the wind. For VRE production, no fuel cost incurs. Nor are they able to store their primary energy and use it in times when electricity production is most profitable.

The system is transformed, shifting away from power plants which can operate on demand towards large shares of generation capacities which rely on favorable weather conditions. At the same time, VRE is produced at (near) zero marginal cost and therefore leads to price drops whenever supply is high, replacing more costly dispatchable generation in the mix (Cludius et al., 2014; de Lagarde and Lantz, 2018; Luňáčková et al., 2017).

Up to date, VRE deployment has mostly been steered through out-of-the-market (OOM) mechanisms that aim at fostering investment. Initially, these instruments were targeted at getting VRE “off the ground”, with governments playing a crucial role in increasing and speeding up the deployment of VRE (IPCC, 2011). Reliable support policies, such as feed-in tariffs or tax credits, were necessary to drive research and development of VRE, thereby reducing their costs and increasing their competitiveness (IEA, 2011). Due to these mechanisms, several power systems have already achieved a high share of VRE in the grid. In Denmark and South Australia, VRE have exceeded all other electricity sources in terms of electricity production (Department of the Environment and Energy, 2019; JRC, 2018). Denmark and Austria further aim at 100% fossil-free electricity systems by 2030, while Germany aims for the same target by 2035 (Federal Ministry of Economic Affairs and Climate Action of Germany, 2023; Government of Austria, 2023; Ministry of Foreign Affairs of Denmark, 2023).

Concerns about the efficiency of deploying VRE through OOM mechanisms have been raised before. (Hogan and Pope, 2017) established that renewable tax credits led to inefficiencies in the ERCOT system, while (Coester et al., 2018) found that OOM VRE expansion reduces supply security in an energy-only market (EOM), due to the downwards pressure on prices that VRE assert. In Europe, concerns for the reliability of the system in the long run are boosted by large parts of the existing coal fleet retiring, due to coal phase-out plans of national governments and low economic profitability as a result of high EU ETS prices (Redl et al., 2020). But concerns go even further: Some question whether a power market can effectively function in a system which is primarily dominated by VRE (Blazquez et al., 2018; Djørup et al., 2018). As a response to such concerns, several European governments have implemented capacity remuneration mechanisms, now effectively also subsidizing conventional generators in addition to VRE (Bublitz et al., 2019). This could, in turn, undo the liberalization of the electricity market, or as (Joskow, 2019) put it: *“It is a slippery slope where subsidies and special contracts lead to more subsidies and more special contracts guided by centralized resource planning rather than decentralized market incentives”*.

1.1 Scarcity pricing

Two different approaches have crystalized in recent years to achieve and maintain resource adequacy: Incentivizing the necessary investments in generation capacities through meaningful scarcity prices or through capacity remuneration mechanisms, such as capacity markets (CMs) (Milligan et al., 2016).

Most power systems have set a maximum price, which is raised whenever load shedding occurs. In EOMs, this price can be based on an estimate of the average value of lost load (VOLL), which aims at finding the most economical solution to the generation adequacy problem (Cramton et al., 2013a). The higher the scarcity price is, the more generation can be profitable, leading to lower occurrences of load shedding events (Stoft, 2002).

Several power systems – such as ERCOT, PJM, the UK and Mexico – have furthermore enhanced the effect of scarcity pricing by implementing a demand curve for operating reserves (ORDC) (Bajo-

Buenestado, 2021; ERCOT, 2013; Hogan and Pope, 2019; Ofgem, 2018). (Hogan, 2013) first proposed to price operating reserves at the value of avoided load shedding, calculated based on the loss of load probability (LOLP) – the probability that balancing reserve demand exceeds the available reserves – and the VOLL. The ORDC price adder for one reserve type can be calculated as follows (Papavasiliou et al., 2021):

$$p_h^{ORDC} = LOLP_h \cdot (VOLL - \lambda_h) \quad (1)$$

With λ_h as the spot market clearing price and p_h^{ORDC} as the price adder. The LOLP is constructed probabilistically using a cumulative distribution function (cdf), with the help of a mean μ and standard deviation (STD) σ that describe past imbalances that occurred after the spot market cleared:

$$LOLP_h = 1 - cdf(R_{tot,h} - R_{min}, \mu, \sigma) \quad (2)$$

With $R_{tot,h}$ being the total amount of available reserve capacity, and R_{min} being the reserve contingency limit, i.e. the minimum amount of reserve capacity withheld. Data on historical balancing activation can be a suitable proxy to determine μ and σ (Papavasiliou and Smeers, 2017).

This price signal also influences the spot market, either directly, in the form of a price adder or implicitly through arbitrage between spot and balancing market (ERCOT, 2014; Hogan, 2013; Ofgem, 2018; Papavasiliou and Smeers, 2017). Scarcity prices therefore do not only occur when electricity demand exceeds supply, but already when the operating reserves available for balancing services begin to run out.

1.2 Capacity markets

Instead of relying on rarely occurring scarcity-pricing events, the regulator can pay the revenue otherwise generated during these events as a capacity premium¹. This payment is usually designed as a monthly payment, and decreases the risk of investing in generation assets through generating more

¹ For example: if there is an average of four load shedding events, during which a VOLL of 10,000 EUR/MWh sets the price, the scarcity revenue for plants which are available at full capacity during these hours would equal 40,000 EUR/MW. The system operator could then decide to pay 40,000 EUR/MW to all providers of firm capacity and in turn introduce a price cap far below 10,000 EUR/MWh.

foreseeable income streams (Cramton et al., 2013a). The regulator sets a reliability target in terms of a loss-of-load expectation (LOLE). Based on the LOLE and the expected peak demand, a capacity requirement can be derived. Often, an auction – the CM – determines the recipients of the capacity payment, based on who can provide the amount of capacity at lowest cost. VRE generators and storage can participate, but are usually de-rated by their capacity credit, which aims to represent the amount of firm capacity the respective plant can provide (Byers et al., 2018). The calculation of the capacity credit is subject to sections 3.2.3.1 and 3.2.3.2.

1.3 Objective

In this paper, we continue the work presented in (Thomaßen et al., 2022), in which we found that there are no barriers to decarbonizing power systems through price signals produced by an EOM. While the previous analysis relied largely on evidence collected from the scientific literature, the work presented here underpins this analysis with the help of electricity market modelling. As many power systems have implemented specific policies to increase the security of supply in their system, we will further investigate the interactions with both ORDCs and CMs. For this, we assess their impact on the market equilibrium under optimal *and* suboptimal calibration.

The remainder of this paper is structured as follows: In section 2, we discuss the relevant literature and further outline the contribution of this paper to the scientific discussion. Section 3 describes the general modeling approach for the different market designs. In section 4, the results are presented and discussed, while section 5 concludes.

2 Previous works and unique contribution

The concerns about whether the electricity market with high VRE shares can function have been addressed mostly qualitatively (Blazquez et al., 2018; Evans, 2017). While (Blazquez et al., 2018) argue that EOMs cannot function with high shares of VRE, due to the need of a conventional plant setting the price for them to run a profit, (Evans, 2017) argues that these systems can function for as long as sufficient amounts of storage are available in the system. The only quantitative analysis known to us is

(Djorup et al., 2018), who modeled dispatch and prices for the Danish power system in a highly decarbonized scenario. They concluded that especially renewable generators were not able to recover their fixed costs. They used an exogenously determined capacity mix, and introduced neither a carbon price nor an administrated scarcity price in the power market, raising the question whether these circumstances are the cause for the low profitability of the installed capacities. This is supported by (Brown and Reichenberg, 2021) who showed that a decline in the market value of VRE technologies can be avoided by a reliance on carbon pricing.

Questions about the right market design for reliability and resource adequacy have been widely discussed in the literature, yet primarily with a focus on supply security, not with regard to the interactions with decarbonization policies (Cramton et al., 2013b; Götz, 2018; Höschle et al., 2017; Khan et al., 2018; Petit et al., 2017; Weiss et al., 2017).

CMs, is often argued, are difficult to calibrate correctly, due to the necessity of forecasting the future capacity demand, and are therefore prone to under- or overinvestment (Hogan, 2013; Yaffe and Tabak, 2018). (Levin and Botterud, 2015) showed further that the introduction of a capacity market led to a decrease in revenue for all generators not participating in the mechanism. Capacity markets were furthermore identified to disfavor VRE (Mays et al., 2019) or storage investments (Askeland et al., 2019). This appears to be in contrast to (Höschle et al., 2017), who found that VRE targets can even be achieved at lower costs if a CM is implemented, and (Coester et al., 2018), who concluded similarly with regard to decarbonization targets.

The scientific literature on scarcity pricing through an ORDC is much less comprehensive. Several case studies found that ORDCs mitigated the missing money issue for dispatchable generation (Liu et al., 2018; Papavasiliou and Smeers, 2017). (Levin and Botterud, 2015) further found that they could achieve a level of supply security similar to a CM. This is in line with (Papavasiliou et al., 2021), who investigated the European system's reliability under different market design settings, including partial and full roll-out scenarios for CMs and/or ORDCs. They concluded that ORDCs were a no-regret option,

as their price increasing effect vanishes, when capacity is abundantly available. In a sense, the study presented here can be seen as a follow up to their analysis, as they investigated transformation pathways with a focus on how reliability policies affected the viability of flexible resources. This analysis goes one step further, investigating the impact of these policies on *decarbonization*, i.e. the viability of VRE investment and the amount ultimately integrated into the grid. A first indication was presented in (Thomaßen and Bruckner, 2024), which concluded that ORDCs can be safeguard the security of supply during the energy transition *without* reducing market-based investments in VRE. The case study, however, featured only two VRE technologies, as well as two dispatchable ones, and therefore neglected the impact of flexibility, for example through electricity storage. The results presented in this case study suggest that flexibility is vital to understand the drivers behind market-based VRE investment and, ultimately, the amount of energy integrated into the grid.

We identified several gaps in the existing literature: So far, there is no analysis of far reaching decarbonization that is achieved through a market-based approach, which includes all relevant technology clusters, i.e. VRE, flexibility and dispatchable generation. To convey a broad picture, we portray the whole transformation process: From a power system primarily based on coal to one, in which more than 95% of electricity demand is satisfied by VRE generation. Analyses that argue against the functionality of the market are either of a qualitative nature, or analyze exogenously determined scenarios on their plausibility. In contrast to this, we focus on the long-term market equilibrium, i.e. an endogenously determined state in which all technologies recover their fixed and operating costs, while no additional investment would be profitable.

A VRE share of 100% is not reached, as we purposefully do not consider zero-carbon dispatchable solutions in our stylized model. This decision was made to contrast VRE with scarce dispatchable generation, the scarcity being determined by the level of the carbon price. As there are, however, carbon-neutral dispatchable technologies (being fueled by biomass, imported synthetic fuels or uranium), a decarbonized system based on 100% VRE does not appear likely. These technologies can be subject to different constraints, such as resource constraints or social acceptance (Thomaßen et al.,

2022). To the extent that they are available, they will bring down abatement costs further. Limiting their deployment allows us, however, to investigate the implications that the paradigm shift from dispatchable generation to VRE and storage has for markets and market design.

Furthermore, model-based analyses of reliability policies have almost exclusively focused on supply security issues and aspects of revenue sufficiency for conventional power plants, even though (Kozlova et al., 2023) found that renewable policies and CRMs in the EU are often in conflict with regard to their objectives. Only one, very stylized example deals with the effects of capacity auctions on VRE and storage revenues (Mays et al., 2019). The question of market design was commonly tackled in a rather narrow sense, contrasting EOMs and different CM designs, with only one example including an ORDC (Levin and Botterud, 2015).

We address these gaps by depicting power systems, in which the investment in all technologies occurs based on market revenues. Going further than previous analyses, we analyze the different stages in which market-based decarbonization takes place and look at the interactions with policies that aim to maintain resource adequacy. The three regulatory scenarios include a conventional EOM, an EOM with ORDC (EOM+ORDC), and a CM. Our focus lies on whether these affect the way that decarbonization takes place, i.e. whether they affect the system's resource mix. The EOM will serve as a reference in this context.

3 Methodology

This section elaborates the modelling approach applied in this case study. Information on the cost data for each technology, as well as timeseries data for load and VRE availabilities can be found in Annex A.

3.1.1 Market design parameters

We constructed three market-design archetypes to investigate the impact on investment and contrast the different outcomes with regard to their efficiency for decarbonization. Some of the parameters, presented in Table 1, have to be chosen, as they are usually pre-defined by the regulator.

Table 1: Market design specific parameters

Market design	VOLL	LOLE target
	[EUR/MWh]	[hours]
EOM	10,000	Not specified
EOM+ORDC	10,000	Not specified
CM	1,000	3

The benchmark design, to which we compare the other designs to, is an EOM with a VOLL² of 10,000 EUR/MWh, which is derived from the technical bidding limit at the EEX intraday market (9,999 EUR/MWh). This design can be interpreted as a *pure* EOM. The only difference to the EOM+ORDC scenario is the implementation of the characteristic demand curve for reserves. At last, we investigate a CM with a fixed balancing requirement, similar to the EOM. A price cap is introduced at 1,000 EUR/MWh, which is a common measure in capacity markets and similar to the upper price limit in most US markets (1,000 USD/MWh), except ERCOT (FERC, 2016). Since the significance of peak prices for investments in generation plants is replaced by a capacity payment, offer caps can be introduced to limit the exercise of market power (Fabra, 2018).

3.2 Model

In this section, we describe the model used to compute the market outcome under each design. The nomenclature used in this chapter can be seen in Table 2. Especially in cases involving an ORDC, an accurate representation of available balancing capacity is essential, so that the ORDC's price effects are neither over- nor underestimated. We therefore rely on the capacity-commitment formulation presented in (Thomaßen and Bruckner, 2024), which takes into consideration the amount of capacity that is able to provide spinning reserves – those capacities that are committed at the respective point

² In this analysis, VOLL refers to the price being raised as soon as load shedding occurs due to demand exceeding the available supply.

in time. How abundantly or scarcely these reserves are available directly influences the reserve price and implicitly the spot price (through arbitrage with the balancing market).

The model is further expanded to include storage technologies, namely batteries, pumped hydro and hydrogen storage. Table 2 displays the nomenclature used in this section.

Table 2: Declaration of sets, variables and parameters

Sets		
h	Hour of the year	
s	Storage (subset of u)	
u	Technology	
Variables and parameters		
$AF_{u,h}$	Availability factor	MW/MW
Cap_{firm}^{eq}	Equivalent firm capacity	MW
Cap_u^{ins}	Installed capacity	MW
Cap^{min}	Minimum capacity requirement	MW
CE_s	Charging efficiency	
Cr_u	Capacity credit	MW/MW
D_h	Demand	MWh
D_h^{max}	Peak demand	MWh
$P_{u,h}$	Power fed to the grid	MWh
$S_{s,h}$	Storage content	MWh
$SC_{s,h}$	Storage charging	MWh
SCR_s	Storage capacity to discharging capacity ratio	MWh/MW

3.2.1 Modelling approach for EOMs

An in-depth description of the model is featured in (Thomaßen et al., 2022). The model depicts a market assuming no flexible demand, yet allowing for involuntary load shedding ordered by the system operator. The objective for modeling the market designs without ORDC is written as a cost minimization, taking into account variable generation costs, fixed costs, annuitized investment costs, as well as load shedding penalized at the VOLL. For markets with ORDC, a term is added to the cost minimization which describes the probabilistically-determined expected cost of load shedding (Levin and Botterud, 2015; Papavasiliou and Smeers, 2017) (compare section 1.1).

Considering the respective shadow prices as market prices, the result is a representation of the market at equilibrium, as it describes a state in which the market revenue is just sufficient to cover the costs of each asset. We rely on a greenfield approach, therefore the market outcome describes the long-term equilibrium. Similar approaches were used by (Tietjen et al., 2016) to model investments in the power market under risk, and (Levin and Botterud, 2015) when modeling the investment in conventional generation under different market designs.

3.2.2 Storage

Storage is expected to be a major component of decarbonized electricity systems (Ruhnau and Qvist, 2022; Zerrahn and Schill, 2017). We therefore expanded the model formulation used in (Thomaßen and Bruckner, 2024) to allow for the inclusion of short- and medium-term storage technologies (batteries and pumped hydro storage), as well as long-term storage (hydrogen storage).

Storage technologies are modeled using a capacity constraint, a storage balance and a maximum charging constraint, similar to the one used by (Quoilin et al., 2017). To keep things simple, we assume that the ratio between storage capacity and charging capacity is constant and discharge capacity equals charging capacity. We furthermore use one round-trip efficiency, as the relevant outputs – the amount of energy used for charging and discharging the storage unit – remain the same as if two separate efficiencies were used.

$$P_{s,h} \leq Cap_s^{ins} \quad (3)$$

$$S_{s,h+1} \leq S_{s,h} + SC_{s,h} * CE_s - P_{s,h} \quad (4)$$

$$S_{s,h} \leq Cap_s^{ins} \cdot SCR_s \quad (5)$$

$$SC_{s,h} \leq Cap_s^{ins} \quad (6)$$

3.2.3 Capacity market

The capacity auction has been modeled as an additional constraint, which enforces a minimum capacity requirement. The different technologies can contribute to fulfilling the capacity requirement, valued at the respective capacity credit. The credit is treated as a parameter in this model, as the slope is usually non-linear for VRE and storage technologies.

$$\sum_u Cap_u^{ins} * Cr_u \geq Cap^{min} \quad (7)$$

This formulation enforces a fixed capacity requirement. We assume a LOLE target of 3h, similar to the one set in Italy, Poland, France and the UK (European Commission, 2018a, 2018b). The minimum capacity requirement therefore equals the fourth largest system-wide load plus the capacity required for fulfilling the balancing reserve requirement.

3.2.3.1 Capacity credit of VRE technologies

The capacity credit of VRE technologies describes the amount of dispatchable generation that can be replaced by the respective VRE capacity, while maintaining the same adequacy level. This is being determined by taking into consideration the correlation between demand and the generation profile (Ensslin et al., 2008). It can be expressed through the difference between peak demand and peak residual remand, normalized to the installed capacity of the respective VRE technology:

$$Cr_u(Cap_u^{ins}) = \frac{D^{max} - (D_h - AF_{u,h} Cap_u^{ins})^{max}}{Cap_u^{ins}} \quad (8)$$

For this estimation, we consider 20 weather years. This way, a wide range of correlations between resource availability and electricity demand is reflected. Increasing the number of years therefore

increases the robustness of the estimated capacity value. On the other hand, it also decreases the capacity value itself, especially at small installed capacities. As more years are considered, it is more likely that one of them includes the coincidence of high demand with (very) low availability. Figure 1 displays this correlation, as well as the capacity credits for onshore and offshore wind. For solar PV, the credit was zero throughout the whole capacity range, as no solar generation was registered during the hour of peak electricity demand.

The capacity credit for onshore (WTON) and offshore (WTOF) wind remains stable for as long as the residual peak remains at the same hour as the total peak. During this period, the credit of VRE technologies is equal to the availability during that hour since each additional MW reduces the peak by 1 MW multiplied with the respective availability. At some point, however, the residual peak starts moving to hours with a lower availability: The residual load in this timeframe is reduced less by additional VRE capacity than the initial residual peak. The capacity credit therefore approaches the lowest hourly availability within the time-series with increasing amounts of installed capacity, as the residual demand during this interval is reduced the least by additional capacity.

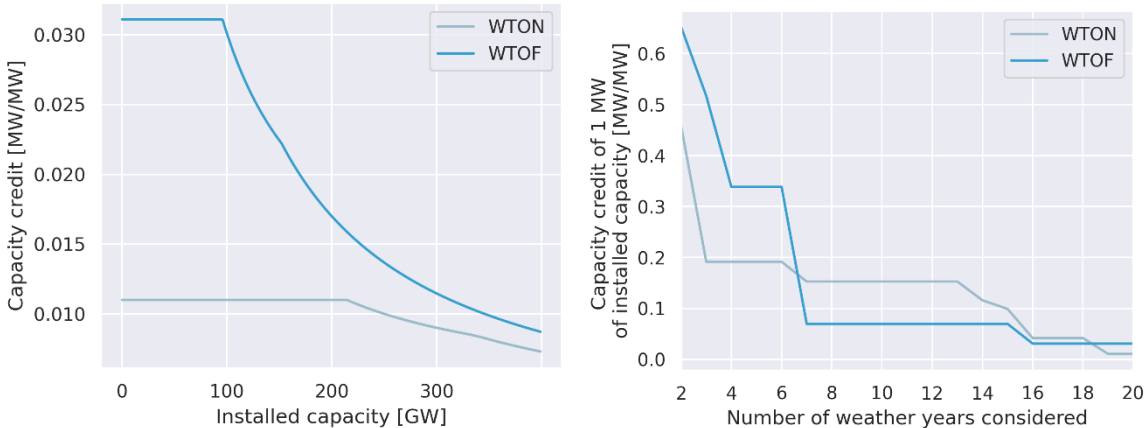


Figure 1: Capacity credit of onshore and offshore wind in Germany considering 20 weather years (left), as well as impact of the number of weather years selected in the calculation process (right).

The capacity credit function is non-linear and non-convex. To avoid approximating the function through a set of piecewise-linear constraints – which would change the problem from a linear to a mixed-integer problem – an iterative approach was used: First, a capacity market is modeled, using a first guess for the capacity credits. Based on the resulting capacities, the credit is recalculated using

the curves presented above. In case that the capacity credit deviated from the initial guess, this step is repeated until the capacity credits for all technologies converged.

3.2.3.2 Capacity credit of storage technologies

We selected an equivalent firm capacity (EFC) approach to assess the capacity credit of storage technologies, as applied in the UK CM (Burke, 2017). The approach aims to determine how much perfectly reliable capacity is needed to replace a certain level of storage capacity while maintaining the same level of reliability. This capacity credit can be calculated as:

$$Cr_s(Cap_s^{ins}) = \frac{Cap_s^{ins}}{Cap_{firm}^{eq}(Cap_s^{ins})} \quad (9)$$

The calculation of storage capacity credits is subject to Appendix B. Based on the results, we concluded that hydrogen storage – due to its long storage durations – functions basically as a perfect substitute for firm capacity. The contribution of batteries was found to be independent of the carbon price, and only dependent on the capacity level of batteries. This indicates that it does not make a difference for their contribution to reliability *how* the battery is being charged – using gas-fired generation or using VRE.

4 Results and discussion

In this section, we first present the results for the reference case – the EOM. Then, we evaluate the impact of different reliability policies, an ORDC as well as a CM, on the market equilibrium. This evaluation includes an assessment of well-calibrated policies, as well as cases where those policies have been calibrated inaccurately, i.e. where we applied a wrong design parameter on purpose. Our focus lies primarily on how these decisions affect the resource mix, and therefore how robust the general market outcome under each policy is.

4.1 System transformation in the EOM

Figure 2 shows the development of the VRE share in the electricity mix as well as the carbon intensity over the full set of carbon prices. One can distinguish several phases: During the first phase, which

covers the range from 0 to 40 EUR/tCO₂, a fuel switch is triggered by the increasing cost of emitting carbon. The system transforms from a lignite-based system, with some gas peakers, to a completely gas-based system at 40 EUR/tCO₂, as shown in Figure 3. Only little VRE investment occurs towards the end of the phase. At the same time, this phase accounts for roughly 65% of the total emissions reduction³. This indicates the significance of phasing out coal for climate protection efforts, even if only replaced with a fuel of a lower carbon footprint.

The range from 40 – 300 EUR/tCO₂ can be described as the *transformation phase*. In this price range, large-scale VRE investment enters the market, changing the structure of the system from primarily based on dispatchable generation to a system which is based on VRE generation and storage. The transformation is driven by increased contribution margins for VRE and storage, which are generated when carbon-intensive power plants are dispatched, due to the high carbon price. As both, VRE and storage, are imperfect substitutes for dispatchable generation, the transformation does not occur as suddenly as the coal-to-gas switch. Instead, two adverse effects are at play which reach a new equilibrium with every increase of the carbon price: The carbon price increases the profitability of VRE. Additional VRE investment, however, reduces the number of hours during which the carbon price is relevant, i.e. when a carbon-intensive power plant is setting the price.

The role of dispatchables shifts to providing ancillary services and back-up/peak-time capacity during the transformation phase. Towards the end of said phase, the efficiency of the carbon price in driving additional clean investments is decreasing substantially, as the number of hours during which carbon-intensive resources are still setting the price is very limited. The system enters a *saturation phase*.

At 1000 EUR/tCO₂, a system based on 96% VRE is reached. While increasing the carbon price from 0 to 300 EUR/tCO₂ induces a VRE share of 83% in the electricity mix, an additional increase by 700 EUR/tCO₂ delivers only additional 13%. Only investment in hydrogen storage remains more dynamic, starting at the end of the transformation phase and continuously displacing dispatchable generation throughout

³ Considering a lignite-based system as the starting point and an almost fully decarbonized system as the target.

the saturation phase. Most of the results will therefore focus on the transformation phase and the early saturation phase, as the changes later on are much smaller.

It is further noticeable that a constant level of capacity from technologies remains throughout the whole transition process that can provide capacity at least somewhat on demand – dispatchable and storage. The capacity level of these combined remains between 85 and 110 GW.

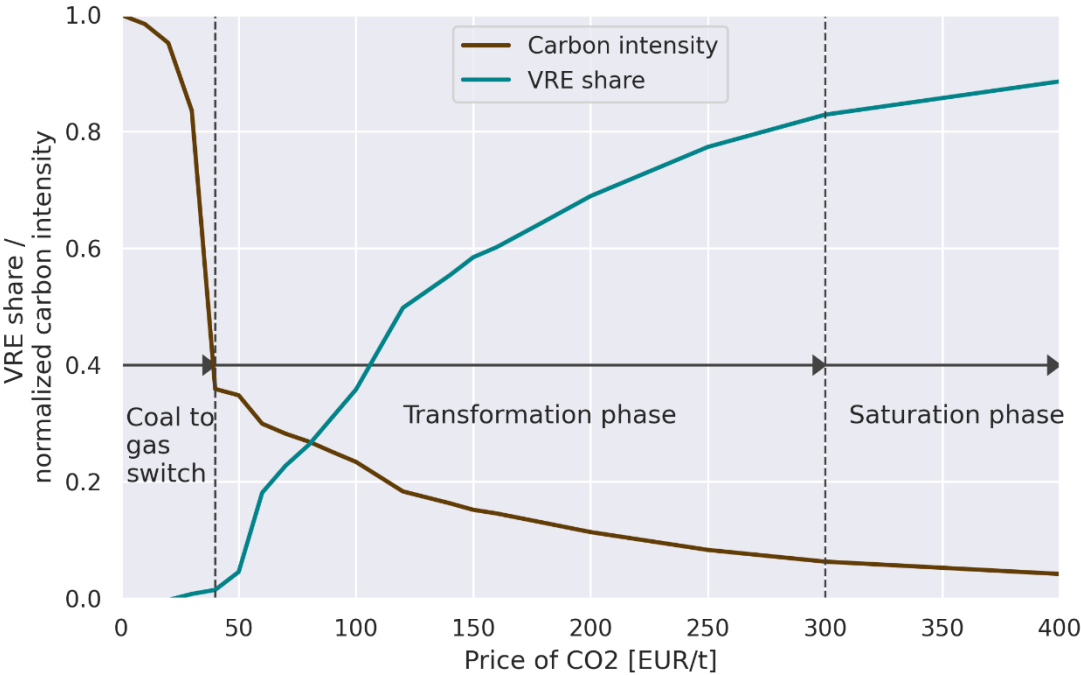


Figure 2: Renewable electricity share at market equilibrium, as well as carbon intensity of the electricity mix at different CO₂ prices.

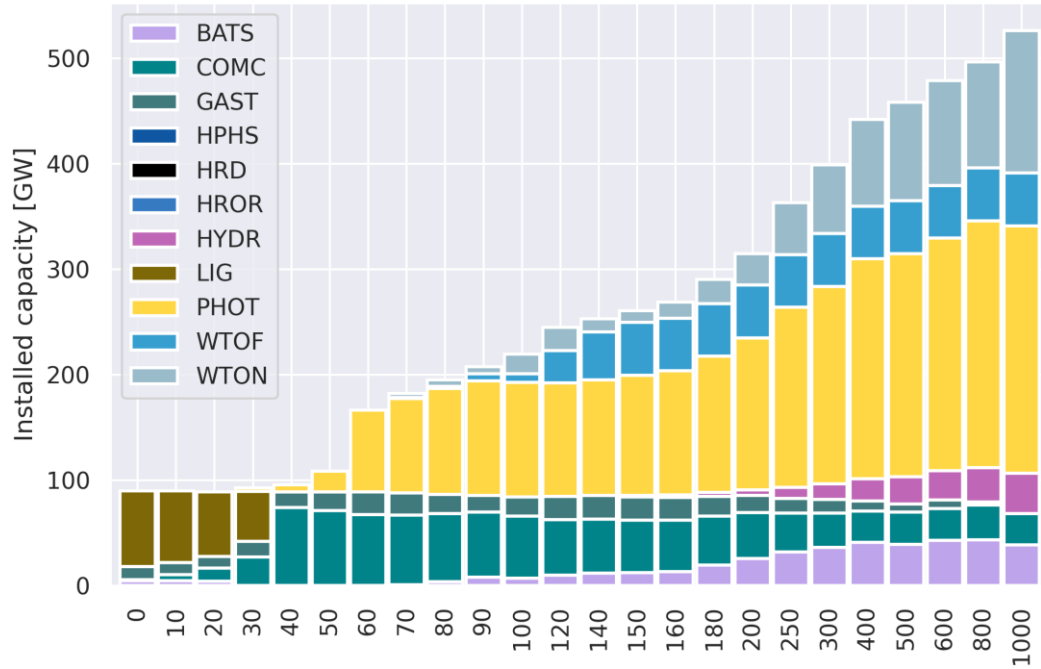


Figure 3: Capacity development in the EOM at long-term market equilibrium with different CO₂-prices. No capacities for hard coal, run-of-river and pumped hydro shown, as no investment in these technologies occurred. Technologies: battery storage (BATS), combined-cycle gas turbines (COMC), open-cycle gas turbines (GAST), pumped hydro storage (HPHS), hard coal (HRD), run of river (HROR), hydrogen storage (HYDR), lignite (LIG), solar PV (PHOT), onshore (WTON) and offshore (WTOF) wind.

4.2 Impact of well-calibrated reliability policies

Figure 4 shows the investment in VRE and storage in the different regulatory scenarios and under different CO₂-prices, while Figure 5 displays the VRE share, as well as the level of curtailment that occurs. The VRE share describes the complement to the share of load satisfied by fossil energy sources and therefore takes VRE generation into account, which is temporarily stored and fed back to the grid later, while considering all losses that occur during that process. It was calculated as $1 - \frac{G_{fossil,tot}}{L_{tot}}$, with the total generation from fossil-fuel-driven power plants $G_{fossil,tot}$ and the total load L_{tot} .

As we can see, all markets achieve similar investment in storage. While EOMs achieve a higher level of storage deployment at carbon prices below 100 EUR/tCO₂, the CM achieves more deployment when CO₂ prices reach 250 EUR/tCO₂ or higher. These differences do not appear to be significant, and might

change with a slightly different calibration – for example of the capacity credits, as investigated in section 4.3.1.

One can further note a clear relationship between storage investment, curtailment and – ultimately – VRE investment. Additional storage does not only reduce curtailment, by integrating more of the available VRE generation into the grid. It further generates additional incentives for VRE, leading to additional deployment. Hence, we see higher VRE shares and lower curtailment in EOMs when storage deployment is higher (below 100 EUR/tCO₂) than in the CM. Once storage investment occurs more in the CM, this reverses. At this stage, storage appears to become more competitive in the CM, as carbon intensive dispatchable generation gets more expensive. The capacity credit appears to be favorable for storage investments as well at this stage, resulting in a beneficial capacity payment. These conditions lower the entry barrier, as less revenue has to be generated through arbitrage.

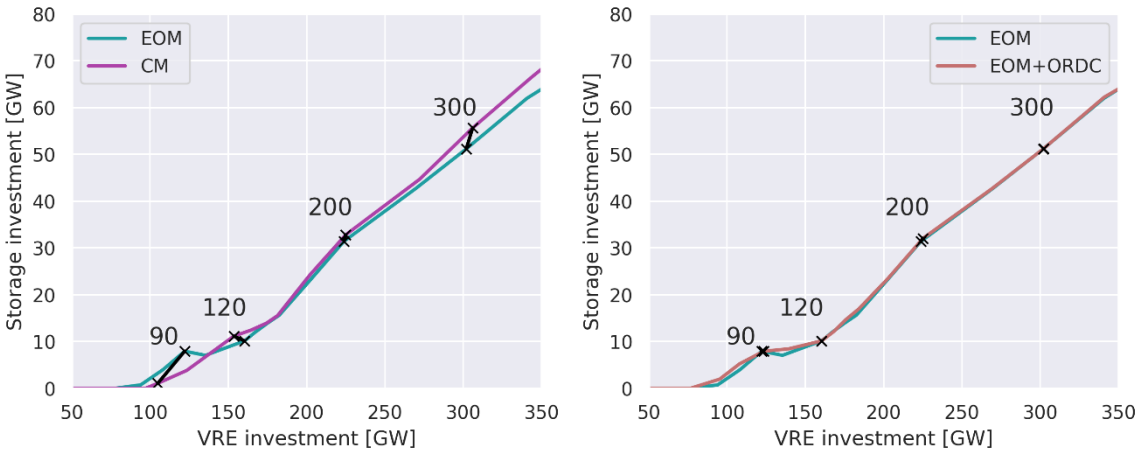


Figure 4: Investment in VRE and storage in the CM (left) and with an ORDC implemented (right). Selected CO₂-prices are indicated through black lines and markers.

The relationship between storage and VRE deployment reflects the additional demand for low-cost electricity that is connected with storage deployment. In hours in which VRE supply is insufficient to satisfy the entire demand for storage charging, the competition for this scarce VRE supply is then

driving up prices. This allows VRE generation to generate additional margins that improve their market value and lead to additional market-based investment.

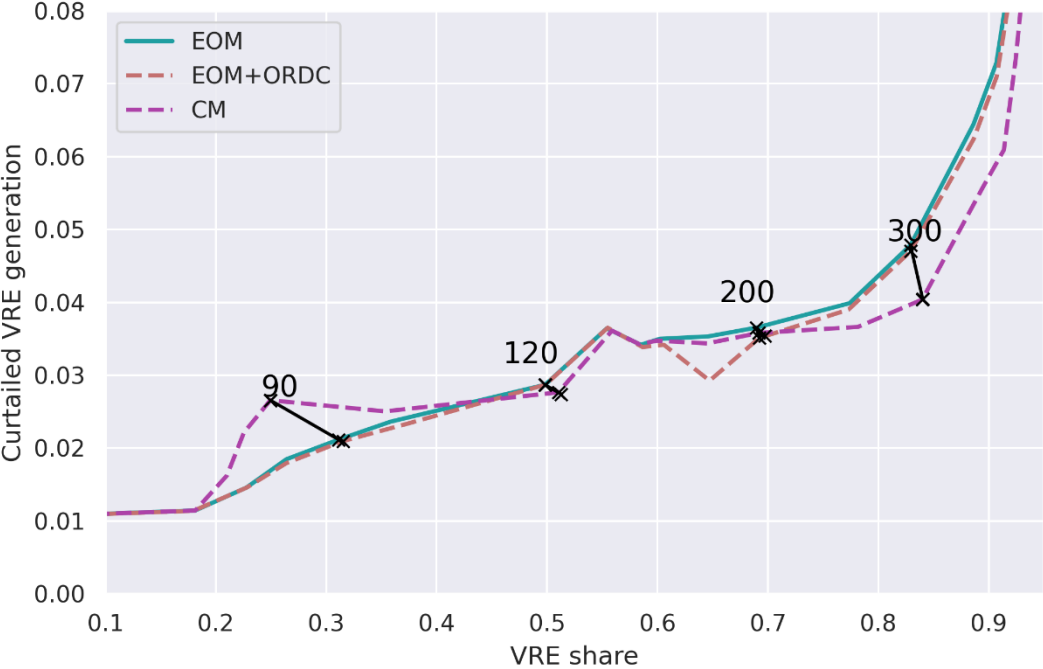


Figure 5: Relationship between curtailment and VRE share under different market rules and at different carbon prices. Curtailment is given as the amount of VRE production which was curtailed. The VRE share is defined as the amount of load, which was satisfied by VRE, directly and indirectly through temporarily storing the energy in storage units.

Figure 6 shows the development of power prices and the effect of the different market designs on it⁴. At 200 EUR/tCO₂, the electricity price reaches 101 EUR/MWh, which fits well with the findings of (Scheller et al., 2019) who estimated a price between 95 and 125 EUR/MWh for the same carbon price in a 2030 scenario for Germany.

⁴ The average power prices were calculated with respect to all payments in the spot, the balancing and the CM (if implemented), and can therefore be interpreted as the average cost of providing electricity to the consumer. In this case study, we are not considering grid charges and other levies and taxes that might still apply.

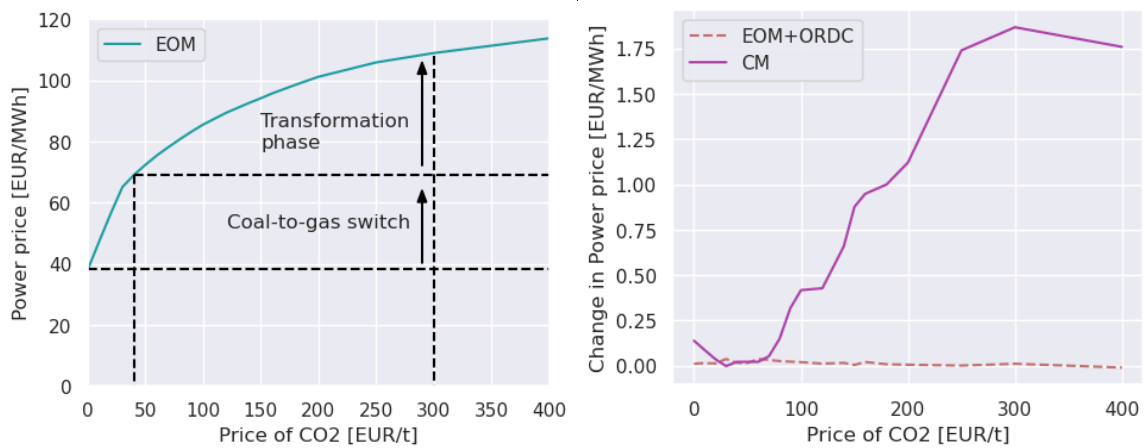


Figure 6: Development of electricity prices under an EOM design (left) and price difference between the other market designs compared to EOM (right).

The largest price increase does not result from the choice of market design, but rather from reducing the carbon footprint. Furthermore, the steepest price increase, from 38 to 69 EUR/MWh occurs in the fuel-switch phase, due to gas plants replacing coal, without any VRE deployment. During the complete transformation phase, power prices rise another 39 EUR/MWh. The coal-to-gas switch is therefore almost as expensive to the end consumer as the transformation of the power system to a VRE share of 82%. At 1000 EUR/tCO₂, power prices in the EOM are reaching 128 EUR/MWh at a VRE share of 96%.

Power prices in the CM are higher than those in the EOMs: The observed price increase due to the implementation of a CM is up to 1.77 EUR/MWh, while there are no substantial price increases due to the implementation of an ORDC. It hints that the CM incentivizes additional capacity in the system, which is mainly financed through the capacity payment. This is further confirmed by the fact that the CM clearing price⁵ remains at the cost of new entry above 100 EUR/tCO₂ which indicates that the marginal unit of capacity is purely financed through the capacity payment. It could indicate an undervaluation of the reliability provided by storage capacity, as this is the point when storage enters the system.

⁵ The shadow price of the capacity market constraint (see section 3.2.3).

4.3 Impact of suboptimal calibration of reliability policies

In this sensitivity analysis, we investigate the impact of reliability policies that are imperfectly calibrated. Our focus lies *not* on the impact on reliability, which could well be substantial in both investigated cases. As we investigate market-based decarbonisation processes, we focus rather on whether wrong calibrations could have substantial implications *beyond* the security of supply, but on the overall generation mix of the system.

4.3.1 Impact of a “wrong” capacity credit on CMs

As the capacity credit for batteries is the only credit which evolves dynamically – while the others remain constant (compare Appendix C) – we chose to perform a sensitivity analysis to assess the impact of selecting a *wrong* capacity credit for this technology. The two scenarios, one over- and one underestimating the credit, are described in Appendix B. The development of the battery capacity credit in the both scenarios, as well as the reference case, can be seen in Figure 7.

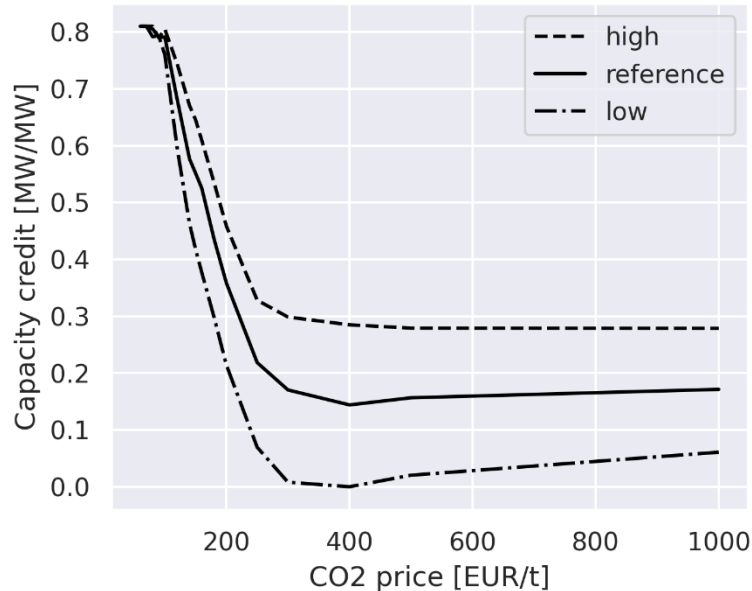


Figure 7: Sensitivities for the calculation of the capacity credit of batteries

This sensitivity is relevant, because as the capacity credit of storage cannot easily be deduced from primary inputs – such as the credit for VRE, which can be calculated from historic generation

timeseries. Instead, the EFC approach has to rely on power system modelling, which is sensitive to primary data inputs, as well as the scope and formulation of the model⁶.

Figure 8 shows the changes in investment for both cases, compared to the reference case. We observe that the market outcome is highly sensitive to the capacity credit that is selected for batteries. If the credit is overestimated, we see much additional battery deployment. Likewise, we see more dispatchable capacity and hydrogen storage deployed when the credit is underestimated. This is a direct result of batteries being less competitive in the capacity market. In addition, more solar PV capacity is deployed if the credit is higher, confirming our previous observation that VRE deployment is directly related to the amount of investment in batteries. At the same time, wind capacity is reduced – only little in the transformation phase but more substantially in the saturation phase. In this phase, batteries replace mostly hydrogen storage. The model shifts between the combination of batteries and PV, as well as of wind and hydrogen storage to maintain a reliable system.

⁶ As systems are considered, which are more complex than the stylized example presented in this case study, it can be increasingly difficult to determine an accurate EFC. Not least because these assessments have to rely on uncertain projections for the electricity demand and the evolution of the capacity mix, resulting in an EFC that changes over the lifetime of a storage plant (Burke, 2017). Results might further vary, depending on which market sessions are considered. Batteries will likely perform better if, for example, balancing markets are considered, due to their fast response capabilities. Considering only day-ahead markets might therefore undervalue the actual contribution to the system's security.

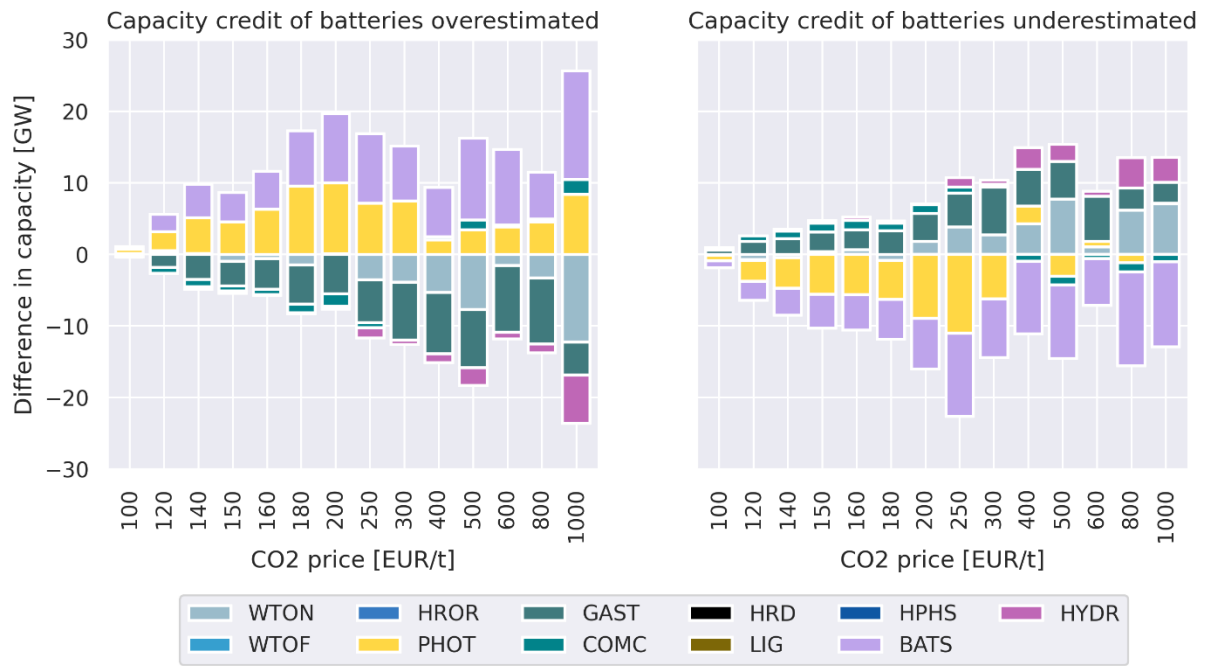


Figure 8: Impact of an overestimation (left) and an underestimation (right) of the capacity credit on the capacity mix at market equilibrium. Only results beyond 90 EUR/tCO₂ are shown, as this is the point when storage deployment starts in our case study.

Changes in the capacity mix translate as well to the generation mix, as can be seen in Figure 9. Additional battery and solar PV deployment increases the amount of VRE generation integrated into the grid throughout the whole transformation phase. In this phase, any reduction in onshore wind generation is more than offset by additional PV generation. Higher battery investment also incorporates more offshore wind generation into the grid on some occasions, even though investment remained stable as the resource potential was already exhausted. This can be attributed to lower curtailment rates. Likewise, a lower battery capacity credit, and lower resulting battery investment, increases the reliance on fossil generation from gas-fired power plants, as less investment in VRE generation occurs, and battery capacity is missing to integrate readily-available VRE generation into the grid.

In the saturation phase, a higher battery credit does not primarily result in solar generation replacing gas-fired generation – as is the case in the transformation phase. They increasingly replace onshore wind generation in combination with hydrogen storage. This is indicated by the fact that PV generation increases much less than wind generation is reduced, likely due to the lower efficiency of hydrogen-

based electricity storage, which is associated with higher energy losses. The fact that a small amount of additional gas-fired generation occurs when the battery credit is higher indicates that batteries alone are not sufficient to achieve the same reliability as the replaced hydrogen-storage capacity. While a higher battery credit leads to higher VRE shares throughout the transformation phase, it may therefore slightly reduce the VRE share in the saturation phase.

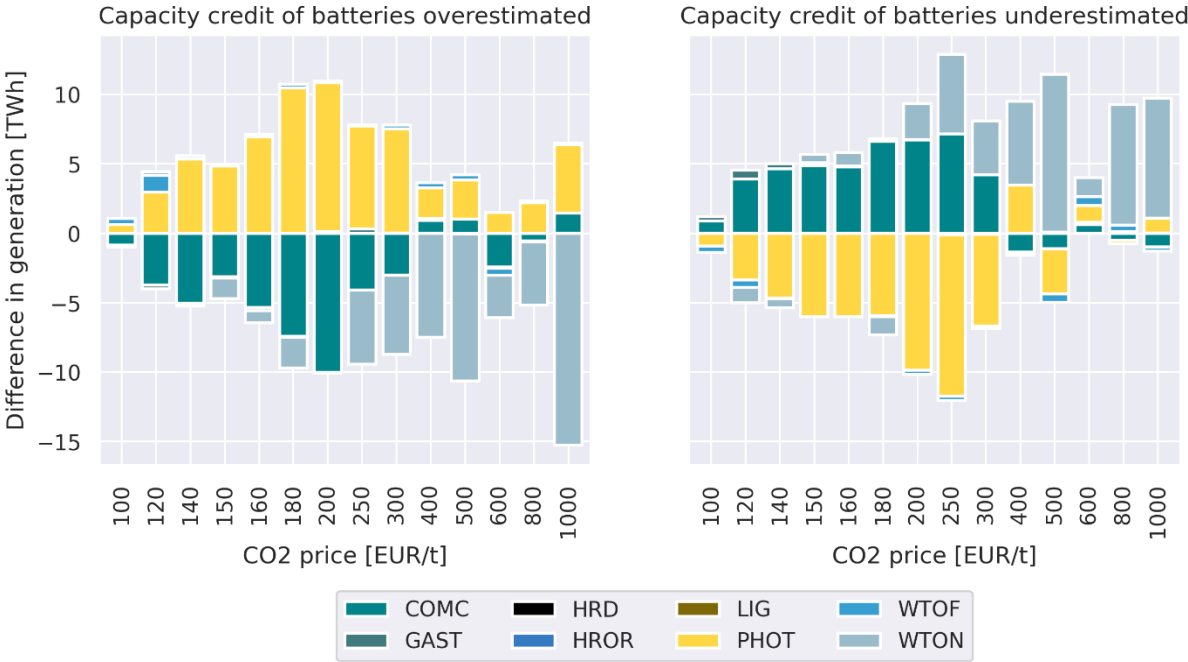


Figure 9: Impact of an overestimation (left) and an underestimation (right) of the capacity credit on the generation mix at market equilibrium. Calculated as the difference between the generation at market equilibrium of the sensitivity minus the one generation of the reference run.

4.3.2 Impact of over- and underestimating the LOLP on the EOM+ORDC

To assess the risk of a wrongly calibrated ORDC, we chose to assess the impact of over- or underestimating the uncertainty in the grid, which affects the LOLP (compare section 1.1)⁷. As the LOLP is calculated with the help of *past* reserve availability, the ORDC’s calibration can be generally considered as less prone to errors compared to the CM, where capacity credits for several technologies, as well as the general capacity target have to be calculated based on projections of the system *in the future*.

⁷ We selected the LOLP, as we assume that the VOLL is the same as the market-specific scarcity price (the price cap).

The LOLP is usually determined through a mean and a standard deviation (STD) that describe the likelihood of a loss-of-load event in a certain hour if a given level of reserves is available (Equation 2). Taking an σ value that is too high or too small therefore allows us to model states when the uncertainty in the grid is either underestimated or overestimated, leading to too-low or too-high LOLP estimates. An underestimation could, for example, occur in a situation when a lot of new VRE capacity came on line in a very short time, as VRE generation increases the uncertainty in the grid, and therefore the LOLP (Thomaßen and Bruckner, 2024). If the LOLP parameters are not updated in time, this could result in an underestimated LOLP. An overestimation, on the other hand, could occur if, for example, forecasting of VRE production improved faster than anticipated. We therefore investigated one case in which the applied STD was half the actual value and one where it is twice as large. These values appear quite unrealistic for real world systems, as they imply that the system operator overestimates imbalances in the grid by 100%, or underestimated them by 50%. This appears to be highly unlikely in a real-world setting.

The results show that the calculation of the LOLP does indeed affect the market equilibrium. A higher LOLP seems to increase the reliance on the combination of storage and VRE in transformation phase, while it leads to rearrangements between individual VRE and storage technologies in the saturation phase. Overall, the changes – compared to the sensitivity analysis conducted for the CM – are, however, much smaller. While changing the capacity credit of batteries regularly resulted in changed investment decisions that affected 20 – 30 GW of capacity (or even beyond), doubling or halving σ results only in changed investment volumes of up to 8 GW, with most values below 5 GW.

Given that the sensitivities investigated for the EOM+ORDC scenario imply an extreme deviation between observed and actual system behaviour, we conclude that ORDCs provides quite a stable market equilibrium.

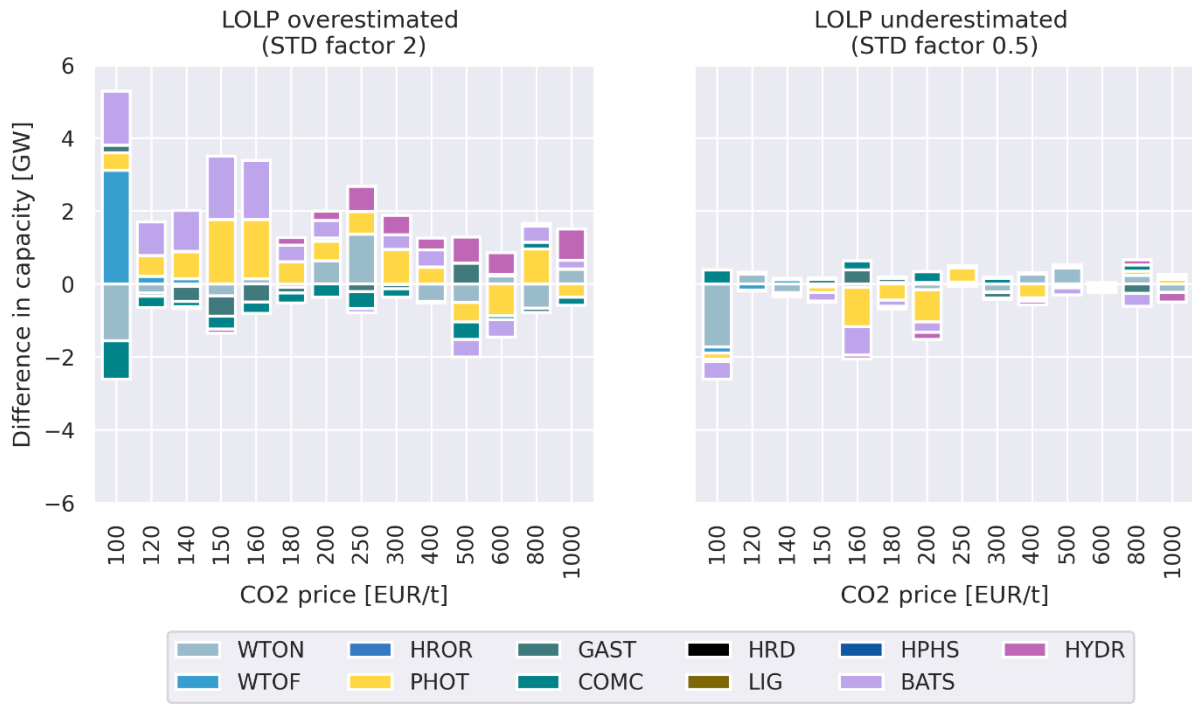


Figure 10: Impact of an overestimation (left) and an underestimation (right) of the LOLP on the capacity mix at market equilibrium.

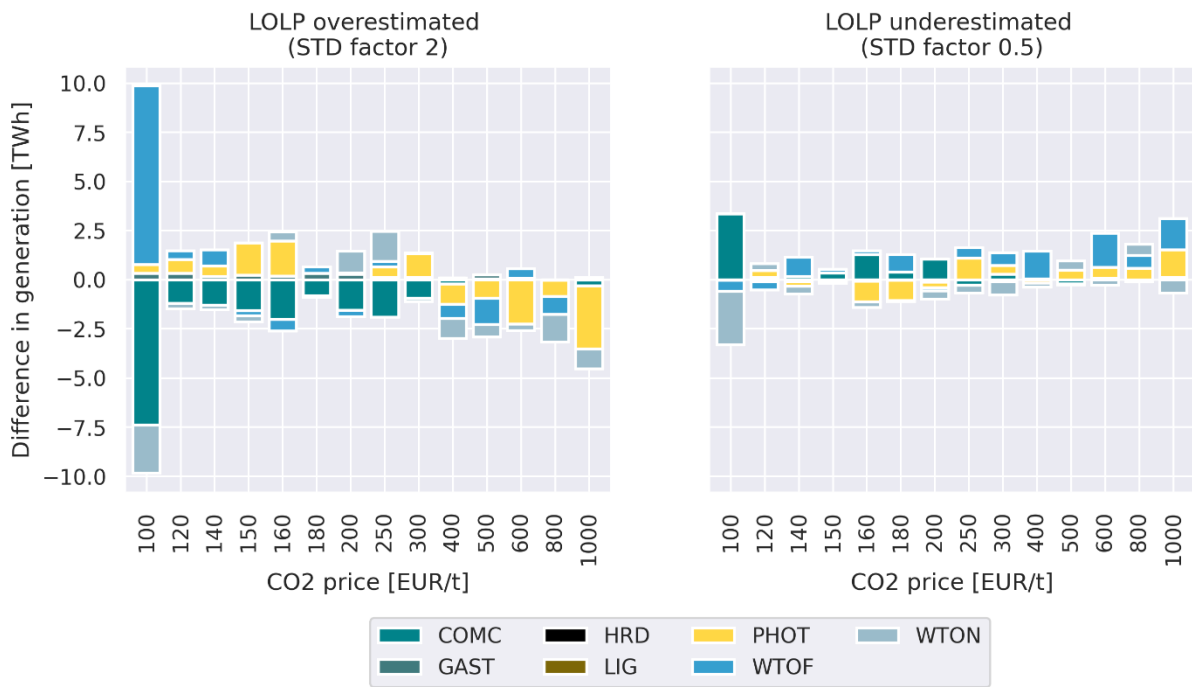


Figure 11: Impact of an overestimation (left) and an underestimation (right) of the LOLP on the generation mix at market equilibrium.

4.4 Limitations to the approach

There are several limitations to the approach chosen for this case study. The first is the fact that we look at the long-term market equilibrium for different stages of decarbonization. In reality, the decarbonisation process takes place as a constant transformation, with additional VRE and storage deployment occurring each year. The system is therefore not able to reach the long-term equilibrium. It will at best reach a short term equilibrium at which the deployment of new technologies might be limited, for example because incumbent plants remain more competitive. These will remain in the market for as long as they recover their fixed costs, therefore this short-run market equilibrium might be skewed towards existing plants. Deployment might further be limited due to non-financial constraints, such as limited availability of skilled workers or production capacities or long planning procedures. Further, fuel and carbon prices evolve dynamically, reaching new levels before the long-term equilibrium can be reached.

These dynamic conditions make it generally harder to predict in which direction electricity markets will evolve. While we assume perfect foresight, these circumstances can hinder investors to assess accurately what an investment will earn in the market. We therefore cannot assume that an investment will automatically be made if the associated revenues exceed a certain threshold. Investors will rather err in their assessments to a certain degree, investing also in technologies that turn out to be unprofitable or not investing as much in new technologies as would be profitable.

The issue of limited foresight applies as well to the regulation of electricity markets, which is particularly relevant for the CM design. Deriving accurate capacity target to achieve a certain LOLE value is much harder in reality, since it involves forecasting the evolution of the system accurately. This relates further to the capacity credit as this credit can change throughout the lifetime of the asset depending, for example, on future penetration levels of the associated technology (Burke, 2017). Further, calculating these credits relies on historical weather data. In times of climate change, these patterns will change to a certain degree, which can further complicate assessing the contribution of VRE and storage to resource adequacy.

We further did not include demand response in our model. From a modelling perspective, demand response would behave similar to either a generator (for load shaving), or a storage unit (for load shifting). Some implications for demand response investments can therefore be derived from our results. Flexible demand might, however, further complicate determining an accurate capacity target in a CM, as it requires knowledge of the amount of “implicit” demand response, for example load from smaller consumers that are reacting to market prices – without taking part in interruptibility or other demand-response schemes. Not considering implicit demand response can lead to a capacity target that is too high, while overestimating its contribution bears the risk of setting an insufficient target.

5 Conclusions and policy recommendations

In this paper, we investigate how market-based decarbonization takes place, both in a conventional EOM, as well as in the presence of reliability policies. One focus was the question whether the EOM remains functional throughout a completely market-driven decarbonization process without the help of OOM measures that compensate potential missing-money issues, as this possibility has been questioned in the past (see section 2).

Our results suggest that market-based decarbonization is feasible without OOM measures and that the EOM is capable of delivering conclusive market outcomes throughout the whole transformation process. At a carbon price of 1000 EUR/tCO₂, the modeled system achieved a VRE share of 96%⁸. This is of relevance as well to systems that rely on OOM measures to deploy VRE, as it means that policy makers can phase out these measures at a later point, if either the carbon price is high enough to support the revenues of the existing VRE investments, or the system is fully decarbonized (rendering the carbon price meaningless). A potential strategy could focus on increasing the market values of low-

⁸ The fact that we stop short of achieving a fully decarbonized system is due to omitting the carbon-neutral dispatchable generation in the setup of the study. This allow us to investigate the shift from a system based on dispatchable generation to one where the main source of electricity is VRE – without predicting the final share of VRE in the system. At each stage, the cost of fossil generation (including the cost of carbon) can therefore be seen as a proxy for the equivalent cost of carbon-neutral dispatchable generation to achieve full decarbonization.

carbon resources by strengthening the carbon price until OOM measures become unnecessary, letting auction clearing prices drop to zero, as proposed in (Thomaßen et al., 2022).

We observe that the transformation process takes place in three phases: The first phase is the coal-to-gas-switch. In our case study, this phase is responsible for 65% of the carbon reduction⁹. This highlights the importance of coal phase outs for carbon-reduction efforts. At 40 EUR/tCO₂, the coal-to-gas switch is concluded and the second phase of the transition starts, with VRE starting to enter the system. Throughout this *transformation phase*, the system transforms from one based on dispatchable generation to one based largely on VRE and storage. Large-scale market-based deployment of storage technologies starts to occur at carbon prices beyond 90 EUR/tCO₂, as the VRE-gas spread is large enough to allow for sufficient arbitrage opportunities. Beyond carbon prices of 300 EUR/tCO₂ and a VRE share of 83%, the carbon price's efficiency in driving further decarbonization was much reduced. An additional increase of 700 EUR/tCO₂ was needed to increase the VRE share by another 13%. In this context, the cost of fossil dispatchable generation can be seen as a proxy for what cost carbon neutral dispatchable generation would need to achieve for another fuel switch. This fuel switch would then conclude the decarbonization process. It is likely that this switch would occur in the saturation phase at the latest, as the cost of fossil-driven generation is extremely high due to the high carbon prices. If this switch should not materialize, other policies could be better suited to complete the transformation in the saturation phase, such as potentially bans on remaining carbon-intensive technologies.

For as long as reliability policies, i.e. ORDCs and CMs, are calibrated well, we find that they have little effect on the general generation mix, which indicates that they can achieve decarbonization as efficiently as an EOM¹⁰. The CM resulted in up to 1.77 EUR/MWh higher costs, than EOM and EOM+ORDC, which achieved very similar costs for the provision of electricity.

⁹ Taking a lignite-based system as the starting point and a fully decarbonized system as the end.

¹⁰ We rely on a cost minimization approach, where the EOM model is the base model, to which additional constraints have been added for the EOM+ORDC scenario and the CM scenario. Therefore, the transformation in the two latter scenarios can only be as efficient, but not more efficient than the transformation in the EOM, since the additional constraints further limit the solution space.

Under suboptimal parametrization, however, we find that CMs achieve less stable market outcomes than ORDCs. Varying only one of several design parameters – the capacity credit of batteries – had a large impact on the generation mix, and affected the carbon footprint. Throughout the transformation phase, a higher credit lead to additional deployment of batteries, but also of VRE as the additional batteries increase the demand for low cost electricity. A lower credit, on the other hand, increased the reliance on fossil generation, as dispatchable technologies were more competitive. We found that changed investment decisions affected 20 – 30 GW of capacity for several sensitivities in the CM, while most shifts remained below 5 GW in the sensitivities assessed for the EOM+ORDC case.

This instability with regard to the CM is concerning, given that CMs rely on a multitude of design parameters, such as the general capacity target, as well as capacity credits for each storage and VRE technology. The capacity credits appear especially prone to errors, as, for example, the number of weather years considered in the calculation process can have a large impact on the credit itself (compare section 3.2.3.1 and Figure 1). Similarly, the storage credit has to rely on modeling exercises, which are affected by the data used to parametrize the model, as well as the scope¹¹ and the formulation of the model. Other parameters, such as the capacity target, are derived from projections on how electricity demand and generation mix might evolve. These circumstances might further provide a basis for extensive lobbying, as profitability in the market might be directly connected to how the capacity credit of one's project is being calculated.

The parametrization process of ORDCs is much more straightforward, as it relies on historical data of system imbalances. For as long as the system evolves without extreme disruptions, ORDC parameters will remain well representative of its state, if they are continuously updated¹². Yet even under these extreme disruptions, the general market outcome proved to be more stable. This indicates that investors can predict an EOM with ORDC better, as competition between the different technologies is

¹¹ For example which market sessions are considered in the modelling exercise.

¹² Massive VRE capacities going on line all at once could be an event that suddenly increases the uncertainty in the grid, as VRE generation is a source of imbalances. Likewise, a sudden breakthrough in forecasting methods could potentially decrease uncertainty.

less affected by the instrument and its concrete design. In addition, the associated price increase was lower in the EOM+ORDC than the one associated with the CM, while CM clearing prices suggested the presence of some overcapacities as soon as batteries entered the system. Previous work has further shown that ORDCs can be calibrated to achieve any level of reliability, even in high VRE systems, meaning that they can fulfill the same purpose as a CM (Thomaßen and Bruckner, 2024). We therefore recommend relying on ORDCs to maintain resource adequacy in low-carbon electricity systems, and systems in transition towards low-carbon electricity sources.

Annex A – Data

5.1 Timeseries data

We use load and weather data from Germany to conduct the model runs (Pfenninger and Staffell, 2016; Staffell and Pfenninger, 2016). A full year is modeled at hourly resolution, as a time-series reduction could distort the impact of scarcity-pricing events, which rarely occur.

5.2 Costs

Table 3 displays the specific parameters for each fuel considered. The specific CO₂ emissions per fuel were taken from (Umweltbundesamt, 2016). Table 4 presents the assumed costs for the different technologies. Since most power systems will likely undergo the transformation process over a time-span of at least 15-20 years, we assumed 2030 costs, based on (Brown et al., 2018a; Schröder et al., 2013). All investment are undertaken based on annuitized investment costs. We assume a discount rate of 4%, a lifetime of 20 years for all technologies and an 85% availability for dispatchable power plants and hydrogen storage. To reflect resource limitations, capacity investment cannot exceed 4 GW for run-of-river plants and 9 GW for pumped-hydro. The limit for offshore wind was set to 50 GW. No other limits were imposed, as we assume that the investment in solar PV and onshore wind stays below technical resource limits.

Table 3: Specific cost and emissions for fossil generators.

	Fuel costs [EUR/MWh]	Emission intensity [tCO ₂ /MWh _{th}]
Gas	21.6	0.19
Lignite	4.0	0.36
Hard coal	10.3	0.34

Table 4: Technology specific costs and parameters based on (Brown et al., 2018a; Schröder et al., 2013), if not indicated differently

Abbreviation	Technology	Overnight capital cost [EUR/MW]	Fixed O&M [EUR/MW/a]	Variable O&M [EUR/MWh/a]	Power Production Efficiency -	Charging efficiency
WTON	Onshore wind	1,182,000	35,000	0	100%	-
WTOF	Offshore wind	2,506,000	40,000	0	100%	-
PHOT	Solar PV	600,000	25,000	0	100%	-
HPHS	Pumped hydro storage	2,000,000	20,000	0	80%	80%
HROR	Run-of-river	3,000,000	60,000	0	90%	-
GAST	Open cycle gas turbine	400,000	15,000	3	39%	-
COMC	Combined cycle gas turbine	800,000	20,000	2	55%	-
LIGT	Lignite plant	1,500,000	37,000	2.6	38%	-
HRDT	Hard coal plant	1,200,000	30,000	2	43%	-
BATS	Battery storage	800,000	12,000	0	90%	90%
HYDR¹³	Hydrogen storage	1,555,749	20,000	0	58%	70%

Annex B – Calculation of the equivalent firm capacity

We determined the EFC for each storage technology, investment level and carbon price by running a capacity optimization based on the results of the EOM runs. The levels of VRE generation are fixed to

¹³ Hydrogen-storage costs are based on the costs for electrolysis, fuel cell and storage in steel tanks for 50 hours. The ratio between electrolyser and fuel-cell capacity has been selected in a way that if both components were to operate at full capacity, the process would be stationary, meaning hydrogen produced through electrolysis would equal hydrogen consumption by the fuel cell. The cost of electrolyser capacity has been based on the lowest cost estimate achieved today (IRENA, 2019), while the costs for fuel-cell and storage capacity have been taken from (Brown et al., 2018b).

the investment level seen in the EOM run. Only one storage technology is added to the model – the one for which the capacity credit is being calculated.

In addition, there is one perfectly reliable dispatchable technology added to the model which serves as the basis for the calculation of the EFC. This technology is based on an OCGT, yet has a much higher investment cost, as to avoid deployment based on economic considerations. To ensure that the same reliability level is achieved in each run, we selected perfect reliability, and therefore did not include an option to shed load.

The model then determines only investment in perfectly reliable capacity endogenously, while all storage and VRE capacities are predetermined based on the EOM runs. The capacity of the respective storage technology is then incrementally increased, solving the model for each capacity level. The decrease in investment in perfectly reliable capacity that occurs at each of these steps determines the EFC.

The resulting capacity credit curve for batteries can be seen in Figure 12. For storage capacity values lower than 5GW, we use 0.816 as the capacity credit. The capacity credit for larger installed capacities is approximated by the function $a \cdot b^{Cap_s} + c$, using the values $a = 0.982017$, $b = 0.999956$ and $c = -0.018$.

For the sensitivity analysis, we applied a b value of 0.999975 to model a case in which the capacity credit was overestimated, as well as a b value of 0.9999 for a case in which the credit was underestimated.

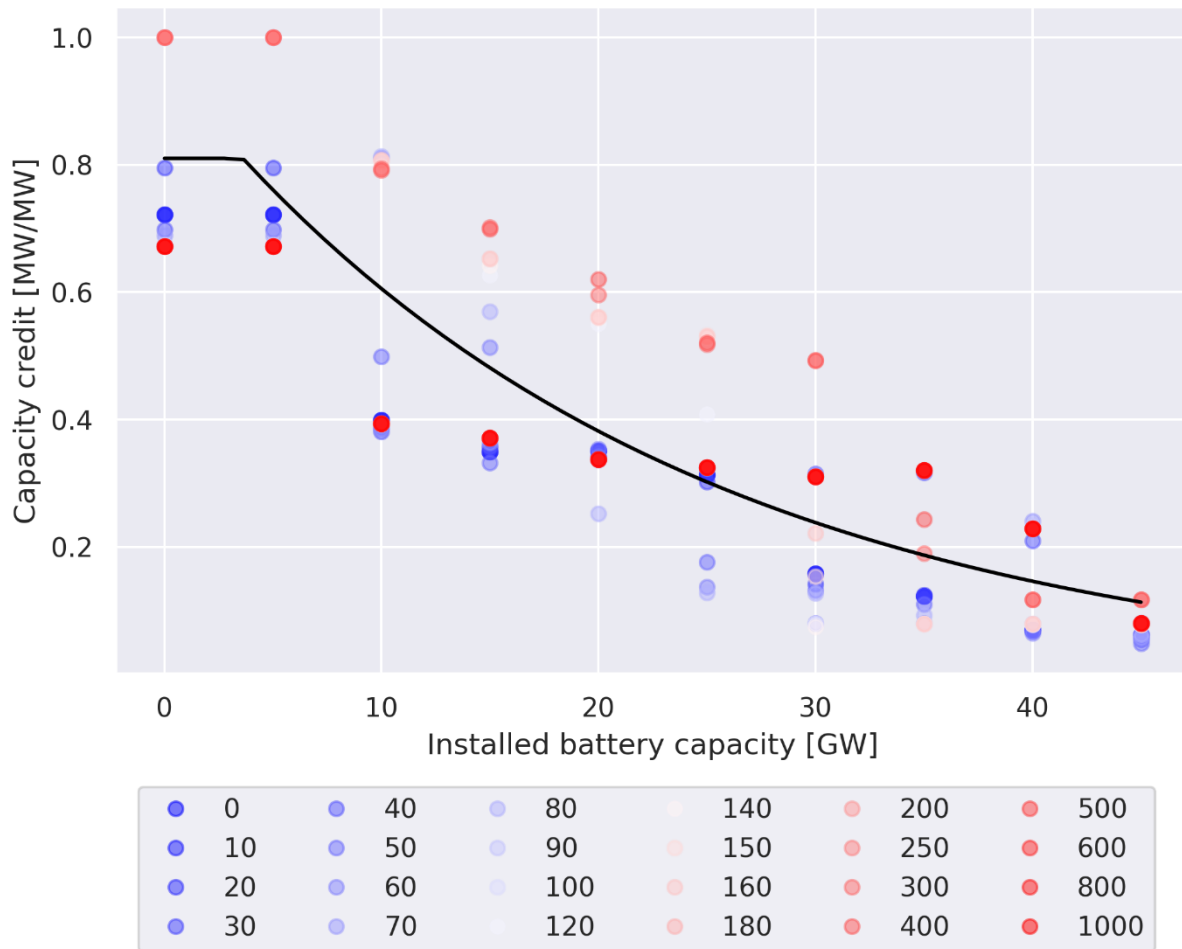


Figure 12: Battery capacity credits determined with EFC approach, as well as fitting function applied. CO2 prices between 0 and 1000 EUR/tCO₂ indicated color of scatter plot.

6 Appendix C – Observed capacity credits for all technologies in the reference case

Throughout the whole decarbonization process, the capacity credits for most technologies remain stable, as shown in Figure 13. Neither onshore nor offshore wind reach installed capacities at which the capacity credit would drop below the initial value (compare Figure 1)¹⁴. Only the credit for batteries changes, dropping from 0.81 down to around 0.15, at which the credit stabilizes for higher CO₂ prices.

¹⁴ In the case of offshore wind, this is due to resource limitations. Onshore wind does not achieve the necessary deployment as its market performance is not sufficient to reach the enormous investment volumes required for a lower capacity credit.

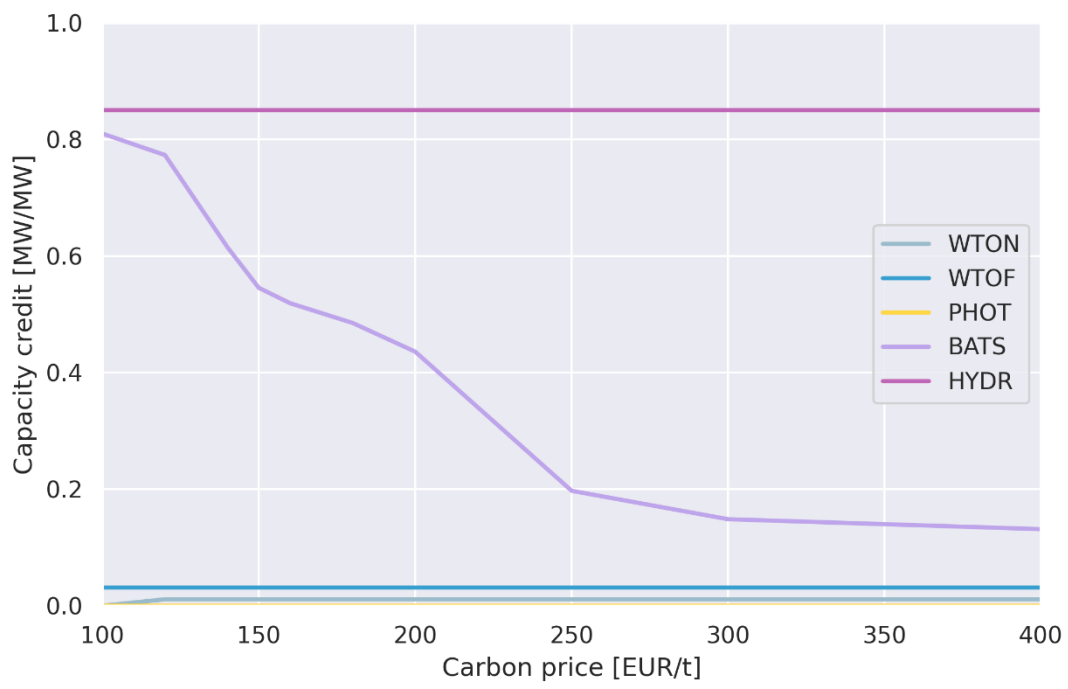


Figure 13: Capacity credit for different technologies. Carbon price interval between 100 and 400 EUR/t shown.

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