STUDY:

QUANTITATIVE ASSESSMENT OF A COMMON THRESHOLD FOR PUBLISHING OUTAGE INFORMATION

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Quantitative assessment of a common threshold for publishing outage information

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Executive Summary

The fifth guidance on Regulation (EU) No 1227/2011 on wholesale energy market integrity and transparency ("REMIT Guidance") envisages the use of "appropriately tested thresholds" for the reporting of outages but does not define or specify what these reasonable thresholds might be. In practice, this means that companies in the same market may apply different thresholds, increasing the risk of inconsistent interpretation and application within the REMIT framework. Developing common, appropriately tested thresholds would increase consistency and reliability for market participants and would support operational practices in electricity generation facilities. Various stakeholders have proposed to choose 100 MW as a common, uniform threshold, which would be also in line with the requirement of reporting unavailabilities of 100 MW and more.

Against this background, a framework has been developed in this study that enables a consistent assessment of potential price effects of outages. The combination of a probabilistic approach with a fundamental pricing model makes it possible to test and analyze price effects taking into account a wide range of uncertainties. The objective of this study has been to evaluate whether 100 MW is a robust threshold for REMIT relevance focusing on the German wholesale electricity market. It has been investigated whether significant price increases (i.e. by more of 5 % of the average base price) are likely to occur. In order to further enhance the validity of the results, the years 2022 as well as 2025 and 2030 have been considered, the latter two each with two scenarios (high and low CO_2 prices).

The following table indicates the range of probabilities of significant price increases for a 100 MW outage in various key technologies, summarizing the results of the five considered scenarios.

Technology	Probability range	
	from	to
Nuclear	0.28%	0.28%
Lignite	0.28%	0.73%
Hard Coal	0.18%	0.72%
CCGT	0.16%	0.73%
OCGT	0.00%	0.62%
Wind Onshore	0.13%	0.16%
Wind Offshore	0.18%	0.36%
Solar	0.06%	0.07%

The probabilities throughout remain below 1% even though some increases in the price effects of plant outages are expected over the next years. Given the variety of considered scenarios, the results underline that a 100 MW threshold is a robust measure to simplify the application of the REMIT criteria. The adoption of such a threshold, proposed also by other institutions, hence contributes to increase consistency and reliability for market participants while ensuring at the same time that major events impacting the price formation on the electricity markets are still adequately reported.

Content

1 Introduction: scope of the study

ACER (2020) provided their fifth guidance on Regulation (EU) No 1227/2011 on wholesale energy market integrity and transparency ("REMIT Guidance"). This guidance provides directions on what market participants should consider in establishing a "framework for the assessment of whether the facts at hand can be qualified as inside information." It envisages the use of "appropriately tested thresholds", which may include "[for] example, qualitative and quantitative (econometrical) analysis to test the likelihood of a significant price effect" (wholesale energy products). ACER does not define or specify what these reasonable thresholds might be, leaving it to market participants themselves to make a decision. In practice, this means that companies in the same market may apply different thresholds, increasing the risk of inconsistent interpretation and application within the REMIT framework.

Developing common, appropriately tested thresholds would increase consistency and reliability for market participants. The concept of an "appropriate tested threshold" would thus be clearly defined, and current uncertainty would be reduced. From a practical perspective, a common, adequately tested threshold would relieve market participants of the burden of conducting such analysis on a case-by-case basis. In this way, the operators of electricity generation facilities would be supported and strengthened, particularly in emergency situations, when operations are driven by health and safety considerations as well as technical and engineering requirements - rather than econometric analysis.

Various stakeholders have proposed to choose 100 MW as a common, uniform threshold, e.g. Nord Pool (2022), BDEW (2019). This would be also in line with the requirement of reporting unavailabilities of 100 MW and more following from Regulation 543/2013 (EC, 2013). This enables an automatic application of an appropriate threshold above which the price effect of an outage has to be deemed "significant", which all market participants can apply in order to comply with the obligations set out in Article 4(1) of REMIT.

The objective of this study has been to evaluate whether 100 MW is a robust threshold for REMIT relevance using a comprehensive, coherent and comprehensible methodology.

The focus has been on the price effect of outages reaching such a threshold. A broad range of different system and market situations had to be considered. This required a probabilistic approach well-rooted in empirical data and a large number of simulations in order to obtain reliable estimates for the relative price effect of capacity outages for a variety of power plants. The main question was how likely significant price effects are – a 5% increase in prices being considered as significant, in line with the guideline on mergers of the U.S. DoJ (1982) and the lower value indicated in a corresponding EU notice (EC, 1997) (cf. also Massey 2000).

For this study a combination of a probabilistic approach that takes into account multiple uncertainties, a fundamental (bottom-up) pricing model, and subsequent post processing was used. It is based on the calculation of fundamental price effects of capacity reductions for different technologies. In the event of an outage, the expected price effect may be determined based solely on the capacity affected by the outage and the corresponding power plant type. The probability that the outage causes price effects that exceed the relative price threshold provides an indicator for the robustness of the proposed threshold. This study focused on the German wholesale electricity market. In order to further enhance the validity of the results, the years 2022 as well as 2025 and 2030 were considered, the latter two each with two scenarios.

In the following sections, the methodology for assessing the price impacts related to a threshold for capacity outages is described first (see chapter 2). Then, the key scenario data and assumptions are presented (see chapter 3) and the assessment outcomes for the proposed 100 MW threshold are discussed (see chapter 4). A short conclusion closes the study (see chapter 5).

2 Methodology for valuating thresholds for capacity outages

As for other commodities, the market price of electricity is determined through the interplay of supply and demand. Among the specificities of electricity are its limited (indirect) storability and the broad range of technologies (and corresponding primary energy carriers) that are used for production. Especially in Germany and more generally in continental Europe, there are currently only very limited storage possibilities for electricity so that the price is mostly driven by the momentaneous balance of supply and demand. Capacity outages affect the supply side, yet also further key factors have to be accounted for.

For a consistent analysis of the impact of capacity outages, their impact on the supply side must be modelled along with other supply variations such as the infeed of renewables or the overall installed capacities. At the same time, also demand variations related to the time of the day or the season of the year or the ambient temperature must be considered. This can be best done through a fundamental electricity market model, which is therefore at the heart of the present methodology (cf. Figure 1). At the same time, the stochastic fluctuations such as capacity outages or variations in renewable infeed have to be modelled adequately in order to assess price impacts in the current and future electricity system. This requires an appropriate probabilistic simulation approach rooted in empirically validated models (cf. Figure 1). These two modules are complemented by a statistical module that enables the consideration of storage as well as imports and exports based on a regression analysis and a post-processing module for assessing the price effects of outages.

Key aggregate characteristics of supply and demand are subject to longer-term changes. Yet they are known at the times of actual operations. To cope with variations in these "boundary conditions" such as installed capacities by fuel and total yearly demand, scenarios were defined (see Section 3.1). However, the (ex-ante unknown) timeseries for demand, infeed and technical unavailabilities of power plants were simulated based on an empirically validated approach in the probabilistic module. This enabled the simulation of different paths for each year and each variable (cf. Section 2.1).

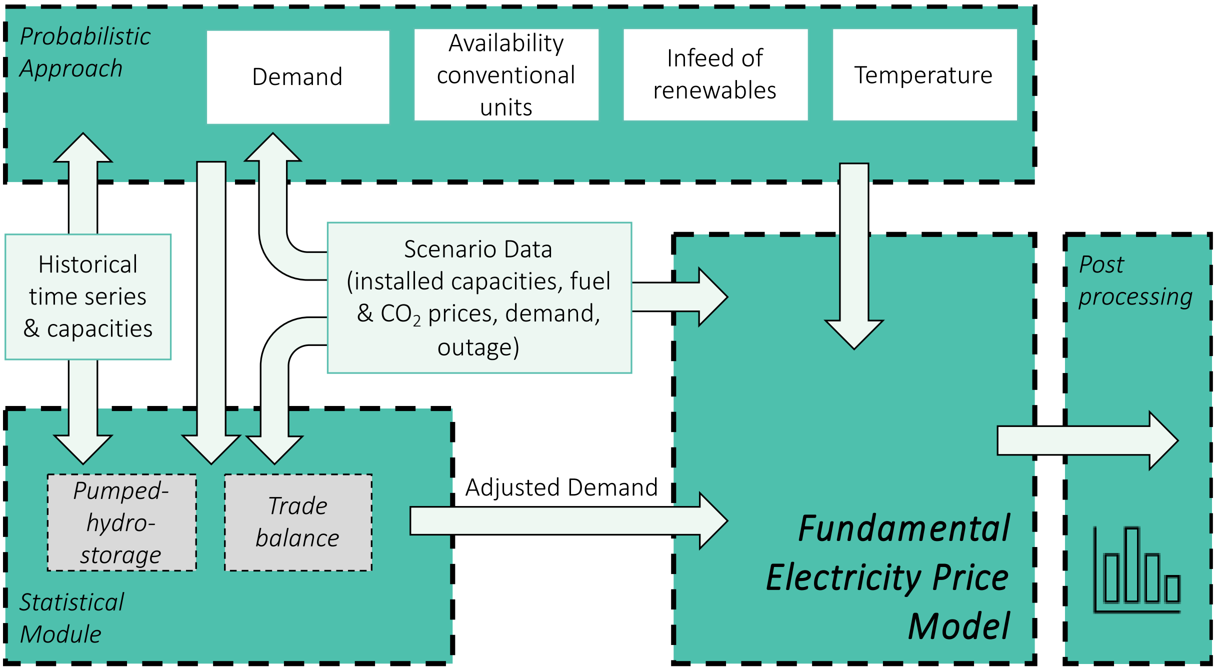

Figure 1: Overview methodology

Outages were simulated through a corresponding increase in demand, because additional generation capacity is needed to compensate for the outage. As outages do not only reduce the supply stack, but may be partly compensated by flexibilities, they had to also be taken into account when applying the statistical module which describes the impacts of available storage and of cross-border trade (cf. Section 2.2).

Subsequently, the simulated values were used to calculate electricity prices without and with power plant outages using the fundamental electricity price model (cf. Section 0). Finally, in the post-processing module, the price effects were calculated and the probability of significant impacts was computed (cf. Section 2.4).

2.1 Modelling the stochastics of supply and demand

Price effects strongly depend on the current situation in the electricity market, such as the current demand level, infeed of renewables, availability of conventional power plant technologies as well as temperature driven must-run of combined heat-and-power units (CHP).

These factors are subject to strong fluctuations at different timescales, including intraday to seasonal variations as well as considerable differences between years. To consider the uncertainty also beyond the historical realizations observed so far, quantile regressions were used to characterize the entire distribution of possible realizations based on the observed data.

Figure 2 shows the general probabilistic approach used for both characterization and subsequent simulation. An adequate database, preferably with open data, is essential for this approach.

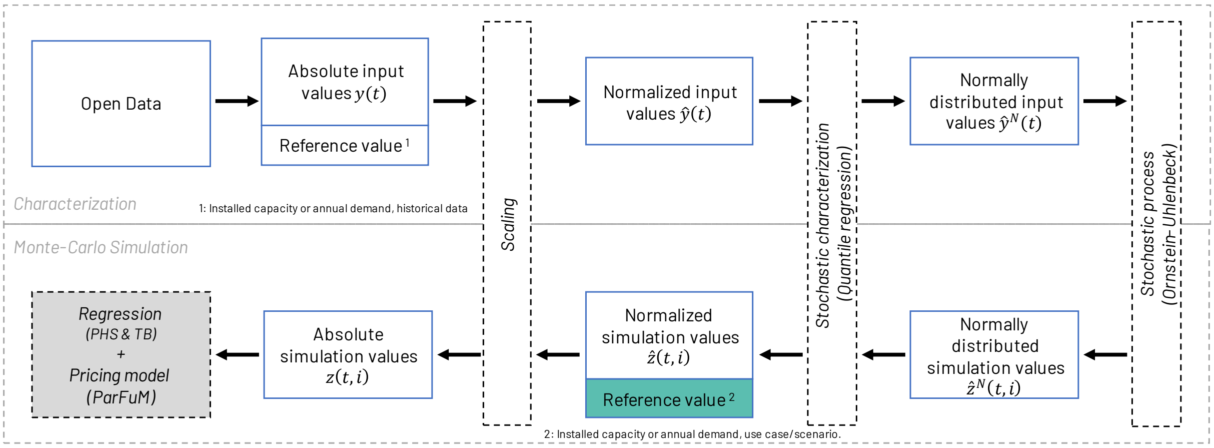

Figure 2: Probabilistic approach

The general approach was applied to all relevant uncertainties, including notably demand and temperature as a driver of demand, availability of conventional units as well as renewable infeed from solar, wind and run-of-river hydro plants. In a first step, the relevant (absolute) input value $y(t)$ (e.g. renewable infeed) is scaled to a normalized input value $\hat{y}(t)$ using a reference value (e.g. installed capacity). After this, quantile regression is used to determine the distribution of the $\hat{y}(t)$ dependent on seasonal, weekly and daily patterns (see exemplary illustration in Figure 3, left side).

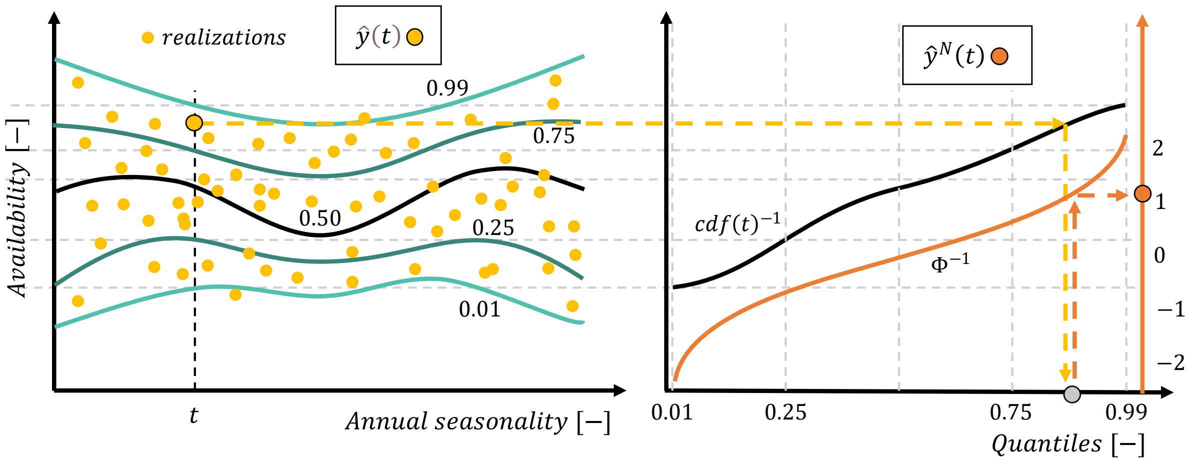

Figure 3: Exemplary quantile regression and transformation depending on season

The derivation of the time-dependent cumulative distribution function $cdf(t)$ from quantile regressions allows the transformation of $\hat{y}(t)$ into normally distributed input values $\hat{y}^N(t)$ via the cumulative distribution function Φ of a normal distribution (see Figure 3, right side). Since the quantile regression captures seasonal, weekly as well as daily patterns, $\hat{y}^N(t)$ only contains fluctuations that cannot be explained fundamentally as well as autocorrelations in the time domain. Based on this remaining time series, the parameters of a stochastic process (Ornstein-Uhlenbeck process, cf. Uhlenbeck and Ornstein, 1930) are estimated, which then enable drawing consistent simulations paths. The consideration of intertemporal effects was notably necessary for the adequate representation of the impact of flexibility options such as pumped storage plants in the statistical module (see chapter 2.2).

Subsequently, these normally distributed simulation values $z^N(t)$ are transformed back to normalized simulation values $\hat{z}(t)$ using the estimates from the quantile regression. Using the reference values for the considered scenario, these values can be transformed into the absolute domain $z(t)$. These simulated absolute values form the input for the following modules, both the statistical module and subsequently the fundamental electricity price model. The simulated factor can also be used to determine the so-called residual demand, which is defined as demand minus feed-in from the variable renewable solar, wind and run-of-river.

2.2 Modelling the impact of storage and international trade

The operation of flexibilities from storage technologies will usually contribute to a smoothing of residual demand. This effect can be captured by a regression model, which uses the current and moving average residual demand as explanatory factors. Based on the available historical observations of storage operations, the corresponding parameters as well as the optimal time window to be used for the moving average may be determined. Given that storage operation is driven also by expectations and that predictions are generally available for future residual demand values, a centered moving average was used as an explanatory variable.

To reduce the computational effort for the fundamental electricity price model (cf. Section 0), it was limited to the sole country of interest (in this study Germany). In that case, cross-border exchanges had to be included as exogenous inputs into the electricity price model. They may be estimated again based on historical data using a regression approach. The trade balance (TB), defined as net exports, depends on the current market situation both inland and abroad. In order to enable a parsimonious simulation framework, only domestic explanatory factors were considered in the regression model, including the infeed of renewable energies, the current demand and the availability of conventional power plants (especially base load power plants).

2.3 Modelling the price formation in the electricity market

This section describes the fundamental electricity pricing model that is used to determine the price effect of different outage sizes. After a brief overview of the main principles, the inclusion of stochastic elements, the consideration of must-run and the simulation of outages are described.

2.3.1 Main principles

The fundamental electricity price model is based on the ParFuM model as described in Beran, Pape and Weber (2019) and Kallabis, Pape and Weber (2016). The model is founded on the principle of the "merit order" or supply stack, where the power plants are ordered by increasing variable cost to form the supply function. Yet instead of a stepwise supply curve, a stepwise linear function is defined based on linear segments defined for the different technology classes considered. Segments of different technology groups may overlap, and they together form the merit order. Compared to the simulation of individual power plant units, this simplified approach enables a much more efficient consideration of uncertainties and analysis of multiple scenarios. Prices are then determined by the marginal costs at the intersection between demand and the availability-adjusted supply function.

In contrast to conventional power plant capacities, the output of variable renewables is only partly controllable – namely through curtailment. Variable costs of renewables are generally close to zero and curtailment even induces opportunity cost related to lost subsidies. Subsidized renewables are therefore positioned in the merit order with the negative amount of their subsidies, implying they are curtailed only when the costs from infeed at a negative electricity price surpass the subsidies received for the feed in. In this way, negative electricity prices can result from the model.

2.3.2 Stochastic elements

While installed capacities and fuel prices only vary across scenarios (cf. Section 3.1), the following elements vary stochastically on an hourly basis in the fundamental model (see also section 2.1):

- Electricity demand
- Temperature (as input for CHP must run)
- Availabilities of conventional power plants
- Infeed of renewable energy sources

As some of these elements also enter the statistical models for PHS and the trade balance, the latter also vary across timesteps and simulations.

For a given sample size N_{sim}, corresponding simulations are carried out for all stochastic elements (cf. Section 2.1) and these values then serve as inputs for the electricity price model. Each scenario is hence simulated N_{sim} times with different paths for the input factors listed above. For each outage, N_{sim} x N_T price effects can thus be calculated per scenario.

2.3.3 Must-run

Technical restrictions such as minimum run times and minimum stable operation limits imply that certain generation technologies like coal or nuclear only partly follow variations in residual demand. This was modelled using a must-run heuristic in the model. Because timesteps are treated independently in the model, two simulation runs are performed. In the first run, must-run is not considered. The results from this first run are then used to determine the share of capacity from the specified must-run capacities that is committed on a daily or weekly basis. This capacity must operate, i.e. its minimum output is set to the corresponding minimum stable operation limit (e.g. 50 % of the available capacity). The remaining capacity share will be dispatched if prices exceed marginal cost.

In addition to must-run from technical inflexibility, must-run is also considered to account for heat delivery obligations for combined heat and power (CHP) units. The heat output of CHP units typically is temperature dependent, which is captured by the following approximate formula (with $temp_t$ the temperature at hour t):

$$f^{MR}(temp_t) = \begin{cases} 0.3, & temp_t > 20°C \\ 1.07 - 0.038 \cdot temp_t, & 2°C \leq temp_t \leq 20°C \\ 1, & temp_t < 20°C \end{cases}$$

This relationship reflects that heat demand is basically linearly decreasing with increasing temperatures. Yet there is a certain fraction of temperature independent heat demand (e.g. in industry or for hot water) and at low temperatures the CHP units reach their capacity limits and additional heat is provided by heat boilers. The function is calibrated to the annual electricity production from co-generation per technology class, which is specified as an input parameter. Additionally, the share of inflexible CHP capacity is given as an input parameter and for inflexible CHP (with a constant power-to-heat ratio), the unused CHP capacity is removed from the merit order. By contrast, the heat-producing units are treated as must-run capacities as described above.

2.3.4 Simulation of outage impacts

The overall price effect of outages is determined by first calculating the prices without outage. The outage is then applied by increasing the electricity demand by the amount of the outage. Modifying the demand in this way is equivalent to reducing the operating capacity by the same amount. To account for the smoothing effect of cross-border exchanges and flexibility from PHS, the relevant regression coefficients[1] are applied to the amount of the outage, reducing its effective impact.

$$outage_{effective} = outage_{total} \cdot \left(1 - (\beta_{outage,exports} + \beta_{outage,PHS})\right)$$

An outage of 100 MW generating capacity might, for example, lead to an increase of PHS production and a decrease in exports, so that the demand that must be covered by German power plants does not increase by the full 100 MW.

[1] cf. section 3.2 for a detailed discussion of the choice of the appropriate coefficients.

This outage impact is valid for any technology that is fully used during the timestep in question. For technology classes that are only partly operating, an adjustment is performed in the post processing (cf. Section 2.4.1).

2.4 Post processing

After calculating electricity prices for the cases with and without outages, a further analysis was performed to determine the statistical likelihood of significant price effects caused by outages of specific technologies.

2.4.1 Technology specific price effects

The (relative) price effect of an outage in each timestep is determined as the deviation from the reference price without any outage in the same timestep divided by the annual average (base price) of the reference price.

$$\Delta P_{outage,itm,t} = \frac{P_{outage,t} - P_{reference,t}}{P_{reference,base}}$$

In this equation, $\Delta P_{outage,itm,t}$ is the price effect of an outage of a technology that is fully operating in timestep t – or in trader slang: the technology is fully “in the money”. If power plant capacity is not operating, an outage cannot influence the price. Consequently, to determine the price effect of a specific technology group, which may not be entirely in the money, the price effect must be corrected:

$$\Delta P_{outage,technology,t} = \Delta P_{outage,itm,t} \cdot s_{tech,t}^{prod}$$

The price effect of an outage is multiplied by the share $s_{tech,t}^{prod}$ of available capacity of a technology class that is producing electricity in timestep t. For example, if 50% of the available capacity of lignite power plants is in the money, in this timestep the price effect for an outage of lignite capacity will be 50% of the total price effect. On the other hand, at night 100% of solar capacity may be in the money, but 0% of it is producing electricity. Thus, the price effect of an outage of solar capacity at night is 0. Note that the correction is also valid in case power plants are not in the money but are producing because of must-run restrictions (see section 2.3.3).

2.4.2 Statistical probability of significant price effects

As described in section 2.3.2, each year is simulated N_{sim} times with different paths for many of the input factors. Thus, for each outage N_{sim} x N_T price effects can be calculated per year.

For each time step and each of the N_{sim} paths, the price effects at the given outage size are calculated and set in relation to the respective base price (cf. Section 2.4.1).

The simulated technology-dependent relative price effects are sorted in ascending order. By interpreting the x-axis as the relative frequency of price effects respectively quantiles with values $\left[\frac{1}{N_{sim}N_T}, \frac{2}{N_{sim}N_T}, \ldots, \frac{N_{sim}N_T}{N_{sim}N_T} = 1\right]$, this corresponds to the inverse cumulative density function (cdf^{-1}) of relative price effects.

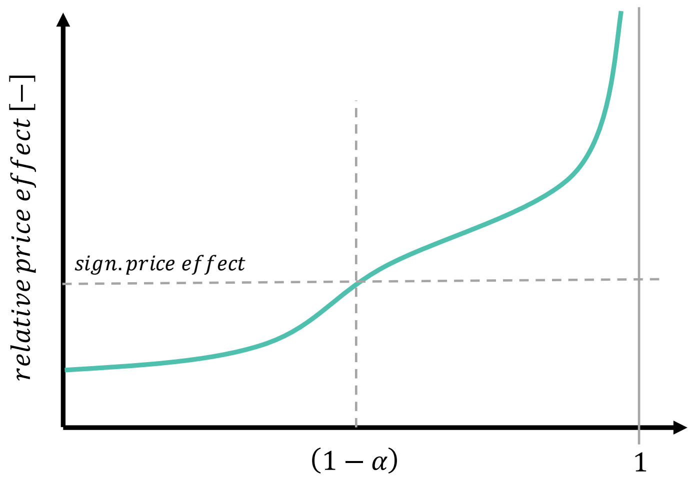

Figure 4: Quantiles (relative frequencies) of relative price effects. Horizontal line as relative price threshold (indicating significant price effects) and vertical line as corresponding confidence level

For a given relative price threshold and outage, the cdf indicates the corresponding probability level of price effects below the threshold. The probability α indicates the probability of prices exceeding a given threshold – defined as significant price effect. This is the main indicator discussed in the result part, Section 4.

3 Scenario data and assumptions

In this study, a price effect is deemed significant if it exceeds 5% of the average yearly base electricity price. A similar definition of significant price increases has been in use for decades in the context of European and international competition and merger regulation (EC, 1997). To obtain sufficient statistical accuracy, 1,000 simulation paths for each year and scenario were calculated, resulting in around 8.8 million data points (relative price effects) each.

Subsequently, details on the scenario data and assumptions are given (see Section 3.1) complemented by results of the statistical analyses (see Section 3.2) that form the basis for the calculations of price effects resulting from a power plant outage of 100 MW.

3.1 Scenario data

In order to investigate whether the proposed threshold is adequate and robust, a range of possible future scenarios was investigated. These scenarios have been constructed based on publicly available input data and analyses. The focus was on the years 2022, 2025 and 2030. An overview over aggregated scenario parameters is given in Table 1, the data used as input are discussed in more detail in the subsequent paragraphs.

In order to investigate variations in the merit order, two CO_2 price levels were considered for the years 2025 and 2030.

Table 1: Scenario overview

	2022	2025	2030
Installed capacities conventional [GW]	71.6	60.7	54.4
Installed capacities renewables [GW]	138.8	166.4	204.2
Total installed capacities [GW]	210.4	227.1	288.6
Net electricity consumption [TWh]	527	542	561
CO_2 Prices [€/t]	69	62 / 82	100 / 140

The fuel prices for these years were based on the assumptions used in the scenario framework 2021 to 2035 for the German grid development plan (Bundesnetzagentur, 2020), for the year 2022 future market prices from European energy trading platforms were used (energate, 2021). Here, average trading prices from the fourth quarter of the year 2021 (October – December) were used to eliminate short term fluctuations while still reflecting approximately the current market situation. For the future years, 2% p.a. inflation was assumed when extrapolating from the last traded values and from the lignite prices given in 2021 values in the grid development plan respectively.

Table 2: Fuel and CO_2 prices

	2022	2025	2030	Unit	Source
Natural Gas	71.73	24.92	27.51	€/MWh	EEX THE Futures Jahre 2022/2025
Oil	40.34	33.98	37.52	€/MWh	ICE Brent Crude Futures (Monthly 2022/2025)
Hard Coal	15.52	11.85	13.08	€/MWh	API#2 Years 2022/2024
Lignite	4.00	4.24	4.69	€/MWh	Scenarios NEP 2035 (2021)
Nuclear	1.70	---	---	€/MWh	Scenarios NEP 2035 (2021)
CO2 Certificates	69.15	72.29		€/t	EEX 4. Period European Carbon Futures 22/25 MidDec
for simulations	69.15	62,29 / 82,29	100 / 140	€/t	

For the installed power plant capacities, the publicly available power plant database of the Bundesnetzagentur served as basis for 2022.[2] For the years 2025 and 2030, data from the ENTSO-E Mid Term Adequacy Forecast (MAF) 2020 (ENTSO-E, 2020) were used (see Table 3).

[2] The power plant database was corrected for the shutdown of the nuclear (Brokdorf, Grohnde, Grundremmingen C), hard coal (Wilhelmshaven, Mehrum Block 3) and lignite (Neurath B, Niederaußem C, Weisweiler E) power plants that have been closed down at the end of 2021. The other capacities for 2022 were determined to the date of 30.06.2022 by interpolating between the values of the BNetzA-database (15.11.2021) and the values used for 2025.

Table 3: Net generating capacities

Net Generating Capacities (MW)	2022	2025	2030
Nuclear	4,056	-	-
Lignite	16,805	14,441	8,934
Hard Coal	14,829	11,140	8,041
Combined Cycle Gas Turbine	19,108	14,811	14,654
Open Cycle Gas Turbine	8,189	6,348	6,280
Fossil Oil	2,548	1,059	840
Hydro Run-of-river	4,315	4,036	4,036
Wind Onshore	57,877	70,501	81,501
Wind Offshore	8,284	10,745	20,757
Solar (Photovoltaic)	59,106	73,300	91,300
Biomass	9,218	7,935	6,635
Waste	1,700	1,700	1,700
Other	4,385	11,175	14,110

Yearly electricity demand was taken from the BNetzA/BKartA Monitoring Report 2021 (BNetzA, 2021) (using 2019 values for 2022) and from the MAF (ENTSO-E, 2020) for the years 2025 and 2030 (see Table 4).

Table 4: Electricity demand

	2022	2025	2030
Net Electricity Demand [TWh]	525	538	547
Number of Electric Vehicles (EV)	762,000	1,751,000	5,751,000
Additional Demand by EVs[3] (TWh)	1.8	4.2	13.8

Table 5 shows the efficiencies, emission factors and variable operation and maintenance (O&M) costs as adopted from the MAF (ENTSO-E, 2020).

Table 5: Parameters of conventional generation technologies

	Efficiency ranges[4]		CO_2 Emission Factor t / Net GWh	Variable O&M Costs € / MWh
Nuclear	30%	35%	0	9.00
Lignite	30%	46%	364	3.30
Hard Coal	30%	46%	338	3.30
Combined Cycle Gas Turbine	45%	60%	205	1.60
Open Cycle Gas Turbine	35%	44%	205	1.60
Fossil Oil	25%	43%	281	3.30
Other	35%	48%	263	2.28

[3] At 2,400 kWh/EV/Year

[4] Based on NCVs (net calorific values)

3.2 Empirical model fitting

Availability, generation and trade balance data used for the linear and quantile regressions were taken from the ENTSO-E transparency platform and cover where possible the years 2015 to the end of 2021. Temperature data is taken from the German Meteorological Service (DWD, 2022).

The availability of conventional power plant capacities depends on planned and unplanned outages. Based on the quantile regression, the entire range of possible availabilities could be determined. Figure 5 shows the mean availabilities for conventional technologies. For all technologies where the available data allowed quantile regressions, there are strong seasonal effects, mainly caused by planned shut-downs due to scheduled maintenance. Due to seasonal variations in demand and renewables, these shutdowns are usually scheduled in the summer season.

The lowest availability could be observed for hard coal plants. While it is likely to be around 80% in winter, it drops to below 60% on average in summer. There are also strong seasonal fluctuations for lignite, but average availability is about 5-10% higher than for hard coal. For gas-fired power plants, availability fluctuations are less strong, ranging from 77% in summer to up to 88% in winter. A slight shift in availability can be observed for nuclear power plants. After a strong decline until May, availabilities are on average increasing again in July.

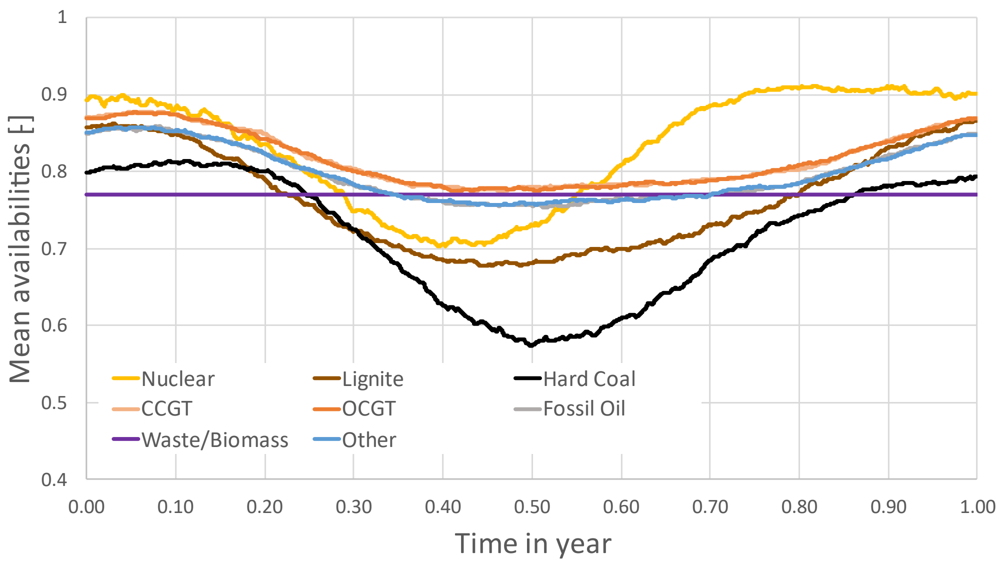

Figure 5: Mean availabilities of flexible technologies

The availability of waste and biomass plants were set at the average of hard coal and gas (CCGT/OCGT).

For renewable energies, the technical availability is less relevant, rather the availability in terms of production capability is primarily driven by fundamental factors such as the current solar irradiation and wind speed determining infeed. While seasonal patterns for hydro run-of-river are estimated on a daily basis, hourly structures were also considered for solar and wind (see Figure 6).

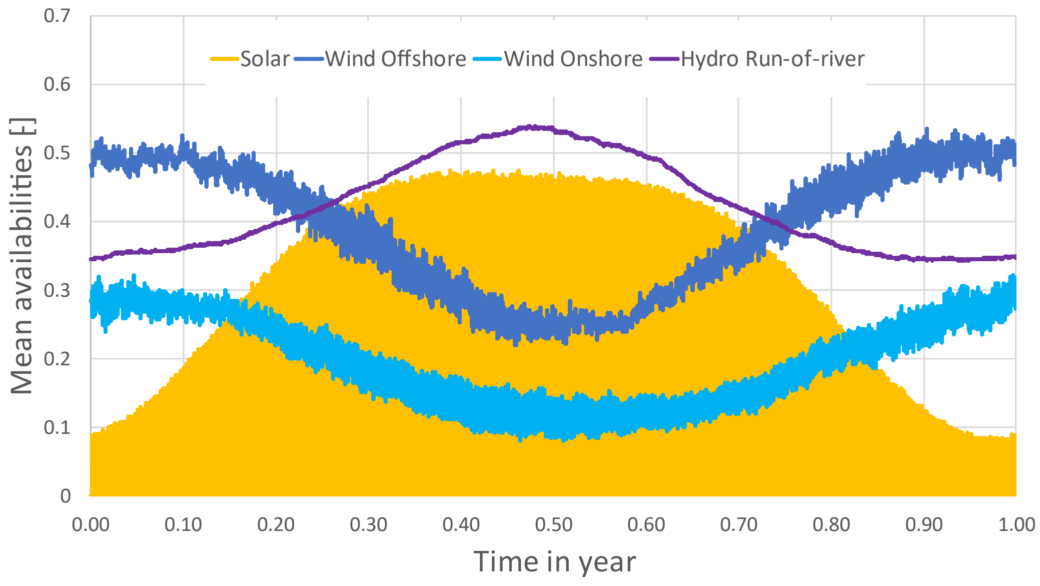

Figure 6: Mean infeed of supply-dependent renewable technologies

In addition to the significantly higher average availability of wind offshore compared to wind onshore, the seasonal pattern for solar is also observable, whereas the day-night variation implies multiple up- and down-running lines that are hardly distinguishable and seem to form a solid yellow shape.

Regarding flexibilities, pumped hydro storage power plants (PHS) are currently the only storage technology in Germany with substantial capacities and significant influence on the energy market. Efficient storage operation takes advantage of price fluctuations, which are largely determined by the variation of the residual demand in relation to a (moving) average value. The regression results obtained from the empirical analysis are given in Table 6.

Table 6: Regression result for pumped hydro storage

	Value
Time window for moving average: T	23
(Constant): β_0	-899.77543
Residual demand: β_1 ***	0.27897
Moving average residual demand: β_2 ***	-0.25517
Adjusted R^2	0.75042

The visualization of the original PHS operation and the regression-based approximation for an exemplary week can be seen in Figure 7. The main operating behavior is well met, but both the upper (discharging) and lower (charging) peaks are partly underestimated.

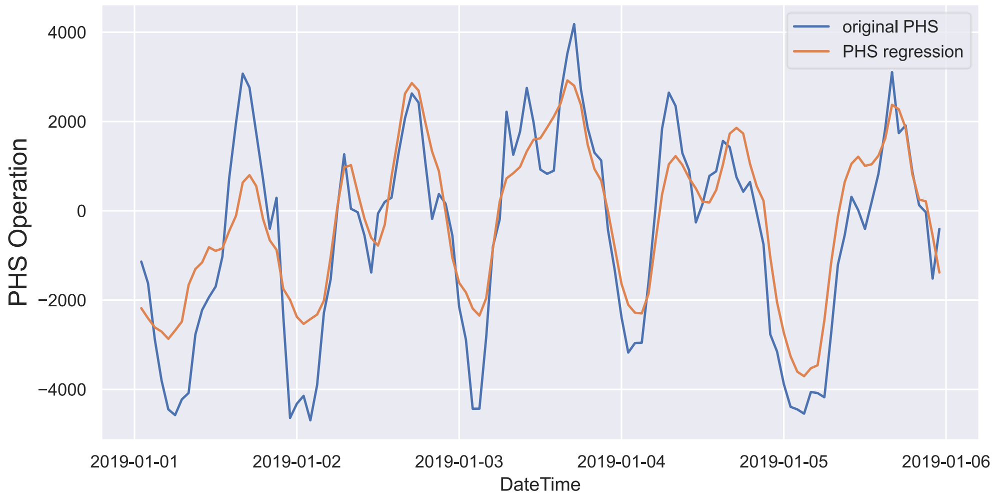

Figure 7: Visualization of the original pumped hydro operation and the regression-based approximation for an exemplary week

Using this empirical relationship, it was possible to estimate the operation without running an optimization model.

Germany is embedded in a European energy system with significant cross-border capacities. To avoid having to explicitly model the surrounding countries, a regression approach was also applied to determine the trade balance. With a limited number of explanatory variables, at least the main determinants and their impact may be depicted (cf. Figure 8).

The empirical results of the regression analysis are given in Table 7.

Table 7: Regression result for trade balance

	Value		Value
(Constant): β_0	-1646.22618	Lignite: β_6 ***	0.15842
WindOn: β_1 ***	0.25494	Nuclear: β_7 ***	0.49960
WindOff: β_2 ***	0.44748	Temperature: β_8 ***	-65.05256
Solar: β_3 ***	0.33214	Hard Coal: β_9 ***	0.33033
RoR: β_4 ***	-1.97518	CO_2 price: β_{10} ***	-13.28585
Demand: β_5 ***	-0.11847	Adjusted R^2	0.60911

Ten highly statistically significant influencing factors could be identified. The explanatory power of the regression model as measured by the coefficient of determination R^2 is lower than for PHS (0.60911 compared to 0.75042). This shows that besides the considered factors, also further drivers determine the trade balance, e.g. the availability of power plants abroad, which is not modelled explicitly.

Figure 8 shows a visualization of the original trade balance for an exemplary week and the corresponding regression-based approximation.

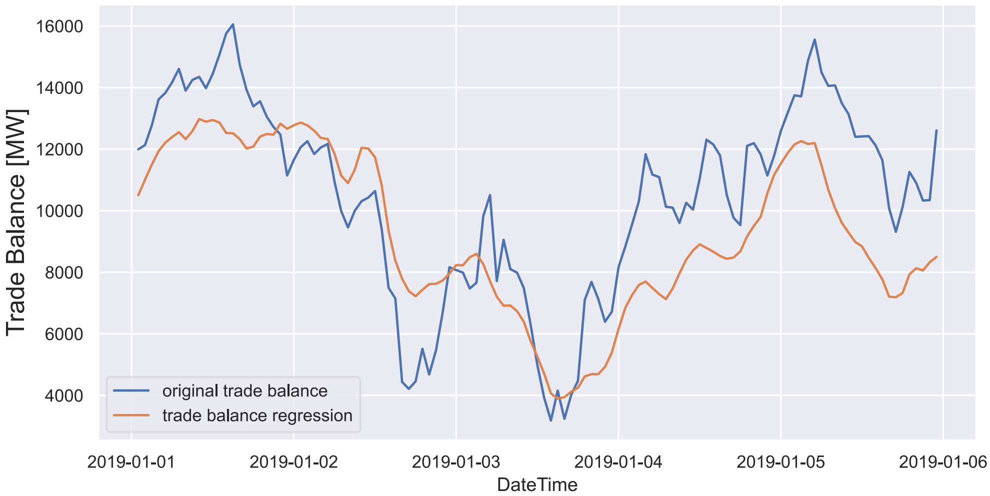

Figure 8: Visualization of the original trade balance and the regression-based approximation for an exemplary week

As detailed in section 2.3.4, the smoothing effects of flexibilities and cross-border trade were also considered in the simulation of outages. In the PHS regression model, the outage affects both the current market clearing and the other time steps. Its impact was thus simulated by a corresponding change both in the current residual demand as well as in the corresponding moving average. Overall, only about 2.4% of a capacity outage are consequently offset by PHS. In the case of exports, the impact of a national outage is similar to the impact of a change in supply or demand that is uncorrelated with changes in neighboring countries. As demand changes are strongly correlated between European countries, rather impacts of changes in renewable supply were considered – here the quantitative effects abroad are much lower than in Germany, given that the neighboring countries are either much smaller than Germany (e.g. Denmark) or have much lower shares of variable renewables (e.g. France). Therefore, the average of the coefficients for wind onshore, wind offshore and solar was taken, resulting in 34.5% of outage capacities being offset abroad. In sum, 36.9% of each outage are compensated by increased generation from PHS and imports.

4 Quantitative assessment of the proposed 100 MW outage threshold

This chapter summarizes the key outcomes of the quantitative assessment. Under the assumptions made for the scenarios, the base price is between €84/MWh (2025, low CO_2 price) and €132/MWh (2030, high CO2 price) and thus significant price effects occurs above €4.2/MWh to €6.6/MWh (see Table 8).

Table 8: Base price and significant price effect

[EUR / MWh]	2022	2025 low	2025 high	2030 low	2030 high
Base Price	114	84	96	112	132
Significant Price Effect	5.7	4.2	4.8	5.6	6.6

In the first subchapter 4.1, the relative price effects of a power plant outage of 100 MW are analyzed. The second subchapter 4.2 focuses on the comparison of probabilities of significant price increases.

4.1 Analysis of relative price effects

Based on the almost 9 million calculated relative price effects for each technology group and scenario, their cumulative distribution (cdf) can be analyzed. The focus was on the upper 1% with the highest potential price effects (cf. Figure 9 and Figure 10). The question was then notably, how probable significant price increases are – with significant price increases being defined as those exceeding 5% of the annual base price (cf. Section 3).

From Figure 9 it is obvious that such significant price effects occur for all conventional technologies in less than 1% of all cases – independently from the technology groups and scenarios considered. The corresponding probability is obtained from the intersection of the horizontal line marking significant prices increases with the cumulative distribution function. The results also show that the probability of significant price effects resulting from a 100 MW outage increases from 2022 to 2025 and 2030.

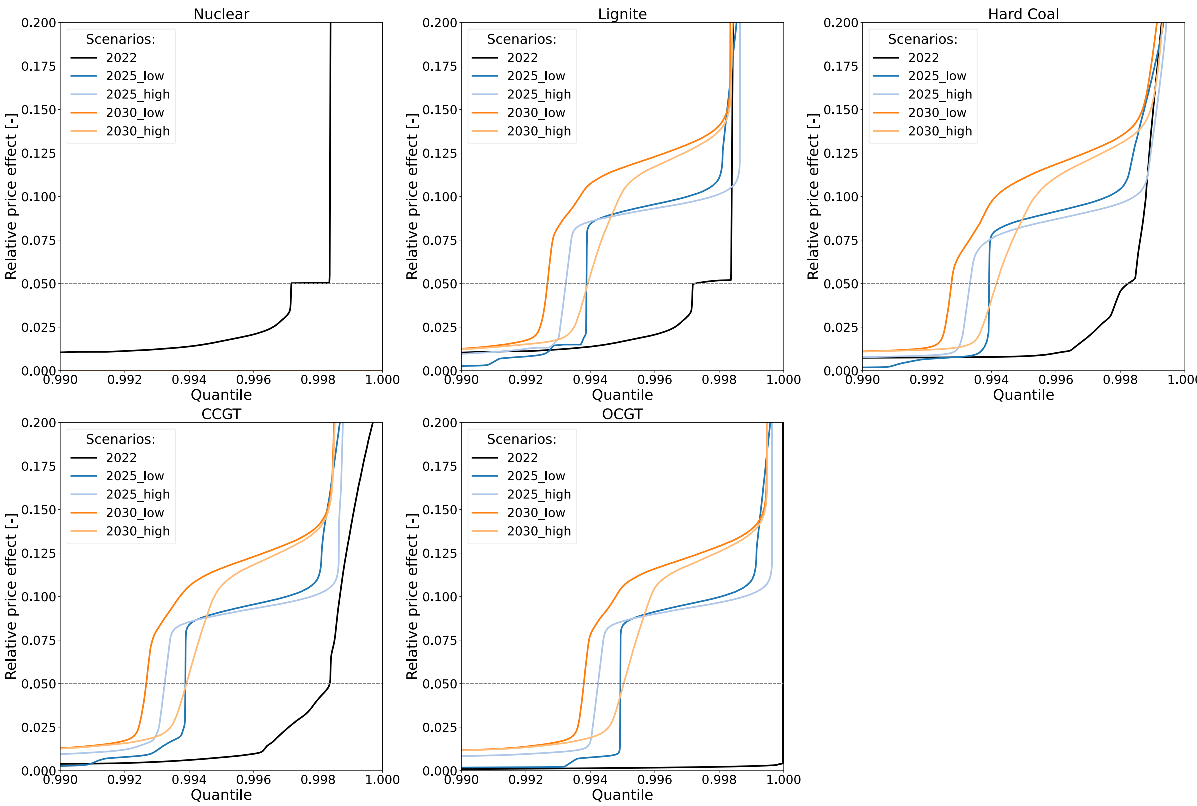

Figure 9: Upper 1% of highest relative price effects for the main conventional technology groups. The defined threshold of 5% relative price effect is indicated by the dashed horizontal line

There are also substantial changes in the shape of the relative price effect curves between 2022 and the following years. Especially the nuclear phase-out end of 2022 leads to major changes in the provision of electricity, which is also reflected in the price effects that occur. Comparing 2025 and 2030, 2030 shows a smoother curve, which can be explained by an increasing overlap of marginal costs of conventional technologies due to rising CO_2 prices. The variation of CO_2 prices has different effects in 2025 and 2030. While an increased CO_2 price in 2025 leads to a steeper curve and less frequent significant price effects, in 2030 the increased CO2 price is expected to lead to more frequent significant price effects. There are only minor differences between the main conventional technology groups.

Compared to conventional base load technologies, the capacity factor (equivalent to full load hours) of renewables is usually significantly lower due to their dependence on solar irradiation and wind occurrence. With decreasing full load hours (wind offshore > wind onshore > solar), also the probability decreases that an outage of 100 MW leads to significant price effects (see Figure 10).

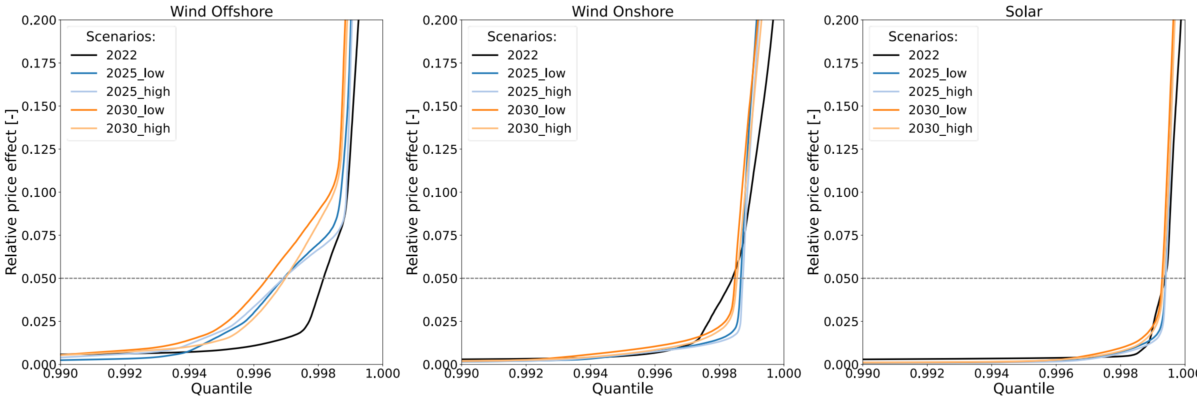

Figure 10: Upper 1% of highest relative price effects for the main renewable technology groups. The defined threshold of 5% relative price effect is indicated by the dashed horizontal line

4.2 Comparison of probabilities of significant price increases

As detailed in section 4.1, a total of almost 9 million timesteps have been calculated to determine the price effect of an outage of 100 MW for each technology group. Assuming that a price effect is significant if it exceeds 5% of the yearly base price (cf. Section 3), the number of timesteps with a significant price effect can be determined. The results are shown in Table 9 as percentage values relative to the total number of calculated timesteps per scenario. They can be interpreted as the probability with which an outage of 100 MW will cause a significant price effect.

The probabilities increase from 2022 to 2030, yet stay below 1% in all cases. Therefore, in more than 99% of all cases, an outage of 100 MW will not lead to significant price effects. The highest probability among the main technologies is 0.73% which is obtained in the 2030 low CO_2 price scenario for lignite and CCGT. This means that on average only in 0.73% of all hours, a 100 MW outage of the corresponding technology will lead to a significant price effect.

The years from 2025 onwards are characterized by higher CO_2 prices and lower gas prices. This brings the marginal costs of lignite, coal and gas-fired power plants closer together (overlapping segments of lignite, hard coal and gas technologies), albeit not leading to a full fuel switch. Consequently, CCGT joins lignite and hard coal as a base load technology from 2025 onwards, and the probabilities for significant price effects are rather similar for the three technologies. Another noticeable effect is that the utilization of OCGT, oil and other increases after 2022 as a consequence of lower installed capacities for conventional plants. Thus peaking plants are utilized more frequently, resulting also in much higher probabilities for significant price increases.

Table 9: Probabilities of significant price changes for outages of 100 MW.

[-]	2022	2025_low	2025_high	2030_low	2030_high
Nuclear	0.28%				
Lignite	0.28%	0.61%	0.68%	0.73%	0.61%
Hard Coal	0.18%	0.61%	0.67%	0.72%	0.58%
CCGT	0.16%	0.61%	0.68%	0.73%	0.61%
OCGT	0.00%	0.51%	0.58%	0.62%	0.50%
Fossil Oil	0.00%	0.36%	0.33%	0.48%	0.47%
Hydro Run-of-river	0.19%	0.18%	0.14%	0.31%	0.27%
Wind Onshore	0.16%	0.13%	0.13%	0.15%	0.15%
Wind Offshore	0.18%	0.31%	0.31%	0.36%	0.30%
Solar	0.06%	0.06%	0.06%	0.07%	0.07%
Biomass	0.29%	0.61%	0.68%	0.74%	0.61%
Other	0.00%	0.51%	0.58%	0.62%	0.50%
Waste	0.29%	0.61%	0.68%	0.73%	0.61%

5 Conclusion

Against the background of the REMIT guidance, a framework has been developed in this study that enables a consistent assessment of potential price effects of outages. The combination of a probabilistic approach with a fundamental pricing model made it possible to test and analyze price effects taking into account a wide range of uncertainties.

Through the probabilistic framework based on quantile regressions, the fluctuations in infeed from renewables, variations in demand and availabilities of power plants were captured via time-dependent distribution functions. Flexibilities through pumped storage power plants as well as the exchange with neighboring countries were taken into account via a statistical model based on regression analysis. They play an important role not only for the fundamental price model, but also for the direct reaction to outages. Technical restrictions such as must-run of technologies driven by heat extraction (CHP) or subject to minimum operating time constraints were also considered.

For the proposed threshold of 100 MW, Table 10 summarizes the probabilities of significant price increases for the key technologies, indicating the range of probabilities across the five considered scenarios.

Table 10: Range of probabilities for a significant price effect resulting from a 100 MW outage in the different scenarios

Technology	Probability range	
	from	to
Nuclear	0.28%	0.28%
Lignite	0.28%	0.73%
Hard Coal	0.18%	0.72%
CCGT	0.16%	0.73%
OCGT	0.00%	0.62%
Wind Onshore	0.13%	0.16%
Wind Offshore	0.18%	0.36%
Solar	0.06%	0.07%

The probabilities throughout remain below 1%, although some increases in the price effects of plant outages are expected over the next years,. Given the variety of considered scenarios, the results underline that a 100 MW threshold is a robust measure to simplify the application of the REMIT criteria. The adoption of such a threshold, proposed also by other institutions, hence contributes to increase consistency and reliability for market participants while ensuring at the same time that major events impacting the price formation on the electricity markets are still adequately reported.

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