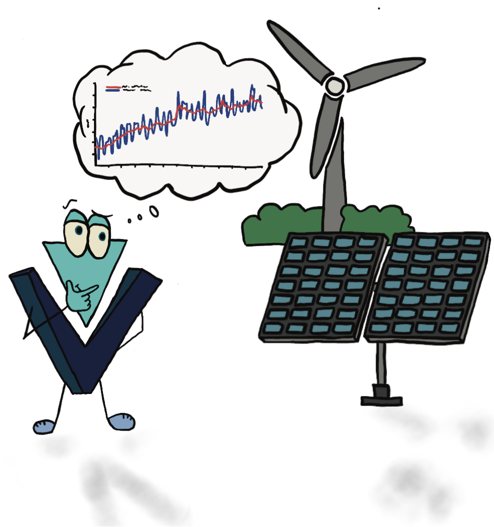
Quantifying and Hedging Weather Risk for Energy Companies



Motivation

Weather risks are one of the greatest challenges that energy companies face in an increasingly volatile world. Renewable energy sources, such as wind and solar power, make planning and operations more vulnerable to short-term fluctuations in energy production and price dynamics. In addition, weather events can significantly impact the demand for electricity and heating. Therefore, a unified understanding of weather risks is essential. This document gives the main theoretical tools to understand and quantify potential non-catastrophic weather risks and the resulting financial impact to future cash flows for energy companies. In doing so, we explain that an important aspect regarding weather risk in the energy context is that it manifests as both a volume and price risk, which appears when the weather affects supply and demand and thus influences market price risks. Moreover, we briefly present some applications regarding renewable energy sources. These applications show promising results and provide a relevant hedging strategy taking into account uncertainties in weather forecasts.

1 Introduction and Definition of the Term Weather Risk

In this section, a definition of the term *weather risk* is provided. First, to distinguish the term *weather* from *climate* and, in particular, *risks arising from climate change*, the following quote should be considered:

> *Think about it this way: Climate is what you expect, weather is what you get. Weather is what you see outside on any particular day. So, for example, it may be 75° degrees and sunny, or it could be 20° degrees with heavy snow. That's the weather. Climate is the average of that weather. For example, you can expect snow in the Northeast in January or it to be hot and humid in the Southeast in July. This is climate. The climate record also includes extreme values such as record high temperatures or record amounts of rainfall. If you've ever heard your local weather person say "today we hit a record high for this day," she is talking about climate records. So when we are talking about climate change, we are talking about changes in long-term averages of daily weather. In most places, weather can change from minute-to-minute, hour-to-hour, day-to-day, and season-to-season. Climate, however, is the average of weather over time and space.*
>
> – NOAA. What is the difference between weather and climate? National Ocean Service website.

Based on the quote above, this document focuses on the impact of *weather* on energy companies. Thereby, the primary objective is to assess the impact of short-term fluctuations rather than the impact of long-term changes in climate conditions. However, since long-term investment decisions (e.g., for district heating) may need to take climate change into account, data sources that are helpful to assess climate change and its impact on energy companies can be found in Section 2.3 of this document.

Next, it is essential to understand the difference between risks due to catastrophic or extreme weather events and non-catastrophic weather. The former include events such as floods, storms, or heat waves. Typically, such events have a low probability of occurrence, but if they do occur, they may cause massive (financial) damage. In contrast, non-catastrophic weather risk refers to small deviations from *normal* or forecasted weather conditions, such as warmer than expected temperatures at a specific location. Additionally, deviations from the forecasted wind speed, the number of sunshine hours, and solar irradiation are also included in non-catastrophic weather risk which is of key importance for energy companies.

In summary, the focus of the document at hand is on the influence of non-catastrophic weather risk for energy companies. In particular, the term weather risk is defined as the uncertainty of future cash flows due to (non-catastrophic) weather. In general, this uncertainty is caused by the spatial and temporal variability of weather, as well as the uncertainties in weather forecasts and often leads to uncertainty about the output of (renewable) energy sources and prices. For this reason, weather risks

can also be classified in the form of volume and price risks under the broader category of *market risk*. As a result, the consideration of weather risk is particularly relevant for power plants and renewable generation plants whose generated volume (volume risk) and capacity are directly influenced by meteorological variables such as wind, solar radiation, or temperature. For example, the generation at wind power plants is highly dependent on the local wind speed, or the capacity of a gas-fired power plant depends non-linearly on the local temperature. In other words, fluctuating power generation due to weather poses a challenge for energy companies, as well as a considerable risk in terms of (adverse) volume changes. In addition to volume risks, there are also significant price risks that arise from weather-related fluctuations. These risks appear when the weather affects supply and demand and thus influences market price dynamics. An example of the impact of weather on demand is the lower consumption of heating energy in unusually warm winters or the higher consumption of electrical energy for air conditioning in very hot summers, while at the same time weather-related production outages, for example at wind turbines, reduce supply, and therefore can lead to significant price increases. It might also happen that the day-ahead electricity price fluctuates by 80% or more within a few days if the weather leads to a sudden increase in demand for electricity or, conversely, to a shortage of supply from renewable plants. This price volatility represents a key risk for energy suppliers, as it leads to considerable financial uncertainty on both the purchasing and sales side.
This document is structured as follows: Section 2 gives an overview about numerical weather forecasts and available data sources. In Section 3, we discuss some methods to quantify and hedge weather risk, while Section 4 provides a short summary.

2 Numerical Weather Forecasts

The results of numerical weather forecasts play a crucial role when it comes to using weather-related information to manage risks and identify opportunities. The basis of meteorological weather forecasts are numerical prediction models that simulate future weather conditions based on current atmospheric observations. In general, these models are based on the mathematical description of physical laws that simulate the dynamics of the atmosphere, including thermodynamic processes. The following sections provide examples about how the opportunities and risks associated with uncertainties in the weather forecast for meteorological variables can be measured at a specified location. As an example, we consider wind speed, but the results can be transferred to other variables (such as temperature or solar radiation), too.

2.1 Prediction paths and model uncertainty

A comparison of individual forecasts that are generated several times a day by different forecast models[1], such as the ICON model (ICOsahedral Nonhydrostatic model) of the German Weather Service or the global forecast model GFS (Global Forecast System), each of which provides a single forecast path, can be used to gain an impression of the tendency of forecasts. In particular, questions such as “What was yesterday’s forecast for today?” can be answered or a comparison of previous forecasts with real-time data can be made in order to assess the accuracy and volatility of a prediction.
Figure 1 shows an example about a comparison of expected wind speed forecasts for a specific location, which were generated from model runs of the GFS model. The black path indicates the current available weather forecast, while the colored paths show the results of model runs, which were calculated up to 7 days before the current forecast.
In general, Figure 1 shows increased volatility for forecasts that have been made further from the current date. Furthermore, the forecasts of the last four days (i.e., previous forecast: day 1 to 4) for the wind speeds for the next 24 hours show a high level of consistency and could therefore be classified as a *good* forecast (i.e., a high level of agreement between the model runs).
However, it should be noted that the individual forecast paths (i.e., simple forecasts of the most probable outcome) generally do not allow any statements to be made about underlying forecast uncertainties, as they do not take all available information into account. More precisely, this type of prediction only provides a single prediction path for each model run, which in turn is very prone to inaccuracies, as even small uncertainties in the initial conditions of the numerical prediction models can lead to large deviations in the results.

2.2 Ensemble forecasts

To overcome the disadvantage of individual prediction paths, probabilistic forecasts are calculated. The predicted probability distributions enable decision-makers to differentiate between various atmospheric conditions or weather events and to react accordingly. To generate probabilistic forecasts, numerical weather models are used to calculate multiple forecast paths by carrying out a large number of simulations with slightly varying initial conditions, model properties, or boundary conditions. In this way, uncertainties and variations in the atmospheric state are taken into account and scenarios (i.e., ensemble members) of different forecasts are generated. Each of these simulations then represents a possible scenario about how the weather could develop in the future, such that an overall assessment of the forecast uncertainties (and therefore weather risk) is possible.

[1] Different forecast models often differ in the parameterization of small-scale processes, the selected grid (i.e., the resolution) or the selected initial and boundary conditions.

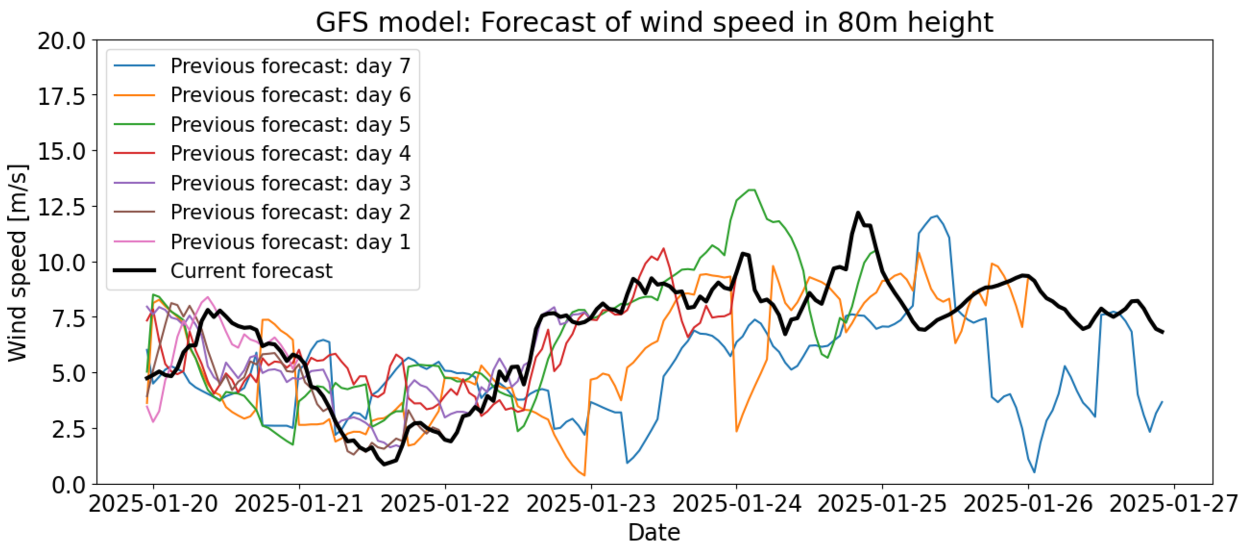


Figure 1: Forecasted time series of wind speeds in 80 m height at a specific location for the current model run (black) of the GFS model and results from model runs of previous days (colored), which were calculated up to 7 days before the current forecast.

It should be noted that although the distribution of ensemble forecasts can in most cases be considered as representative of the actual possible events that could occur, this does not necessarily have to be the case. Nevertheless, this probabilistic approach offers a more comprehensive framework for weather risk assessment compared to individual forecast paths (i.e., using the expected value), especially for weather events with large impacts and high uncertainties[2]. Figure 2 illustrates an example of ensemble forecasts for wind speeds. The blue lines correspond to the results of the various ensemble members. Overall, the ensemble paths show a relatively low dispersion for the first 24 hours, such that one could conclude that the situation (i.e., the wind speed at this location) is well predictable. However, when assessing the forecast uncertainty, one should also compare results between different models and consider historical weather data. In Figure 2, the forecasts for later points in time show a higher dispersion, i.e., there is a higher degree of uncertainty regarding the forecasted wind speeds[3].

2.3 Seasonal forecasts and climate data

This section briefly discusses available data sources for seasonal forecasts, which in particular can be relevant for district heating planning, as well as data on extreme weather events (such as flood indices), and results from climate models. Seasonal forecasts from different models[4] provide a long-term outlook (i.e., forecasts for up to 7 months) on atmospheric conditions (e.g., temperature) and, in particular, can give an impression about how atmospheric conditions will behave during the next 5-7 months compared to *normal conditions* (i.e., climatological averages of the last 30 years). For instance, such forecasts can be used to estimate whether the temperatures of the upcoming winter will be warmer than usual on average. The data is available at a 6 hour temporal granularity. It should be noted that, in contrast to short-term weather forecasts, the data is typically available in a coarser horizontal and temporal resolution and the forecasts are made based on changes in the large-scale, and rather slowly fluctuating components of the atmospheric system (such as the jet stream). This differs from weather forecasts, where predictions for the next few days can be much more precise at a local level. To quantify forecast uncertainties, ensemble forecasts and in particular comparisons of different models can be used. Furthermore, global climate projections[5] (available in daily and monthly resolution), which are typically generated from a large number of model runs from various climate models, form the basis for assessing climate change. Generally, these data can be used to enhance understanding of the climate system and to estimate uncertainties related to the impacts of future climate change. For insights into the influence of climate change on energy generation systems, please refer to Chapter 6: Energy Systems of the IPCC Sixth Assessment Report of Working Group III: Mi-

[2] In addition to ensemble forecasts, it is also advisable to use forecasts of different models and previous days/hours and to compare the forecasts with measurements (e.g., using a suitable dashboard) in order to obtain the most comprehensive impression possible of the uncertainties/risks.

[3] For a more precise assessment of the uncertainty, it can be helpful to compare the forecast with statistics on weather conditions over the last few decades, too. For example, an assessment could be made as to whether *unusual* meteorological conditions above/below the norm are present.

[4] Cf. https://cds.climate.copernicus.eu/datasets/seasonal-original-single-levels?tab=overview and https://cds.climate.copernicus.eu/datasets/seasonal-postprocessed-single-levels?tab=overview

[5] Cf. https://cds.climate.copernicus.eu/datasets/projections-cmip6?tab=overview

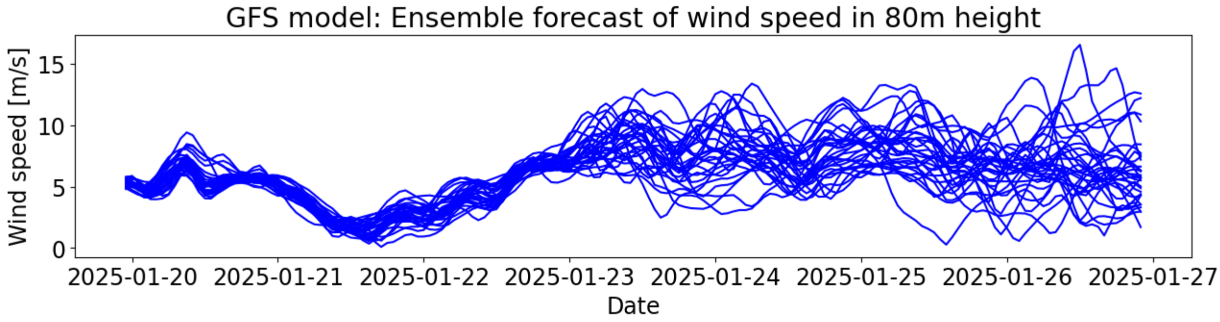


Figure 2: Shown are ensemble forecasts of wind speeds at a specific location for the current model run of the GFS model.

tigation to Climate Change[6]. Additionally, climate-relevant indicators for the energy sector are available[7], which include data such as electricity demand and power generation from various renewable sources (e.g., wind turbines, solar energy, and hydropower). They can be used to study, for example, the role of temperature on demand or the variability in renewable energy production due to climate-induced changes. In conclusion, a few data sources are briefly mentioned here that can provide insights into the risks of extreme weather events, such as floods or extreme precipitation. These include climate extreme indices and heat stress indicators derived from CMIP6 global climate projections[8] and heat waves and cold spells in Europe derived from climate projections[9].

2.4 Historical weather data

For the sake of completeness, this section provides a brief overview of publicly available sources for historical weather data, with a particular focus on the ERA5 reanalysis data, which is provided by the ECMWF as part of the Copernicus Climate Change Service[10]. The ERA5 data provides a globally available dataset for climate and weather over the past eight decades (i.e., from 1940 to the present). The data has a horizontal resolution of approximately 25 km and provides hourly values of atmospheric variables. Reanalysis combines model data with observational data from around the world to create, globally, a complete and consistent dataset of weather variables with a hourly resolution. This dataset can be used, for example, to conduct detailed analyses of various weather phenomena, gain a better understanding of weather events, or analyze long-term climate trends. Furthermore, comparing current conditions with a climatology can provide insights into whether an unusual weather situation for a specific season is occurring.
Other sources for historical weather data can be found here: German meteorological service - Climate Data Center[11] and NOAA - Climate Data Online[12].

3 Quantification and Hedging of Weather Risks

In this section, we provide methods about the quantification and hedging of weather risk, addressing the impact of weather on (renewable) power generation (i.e., volume) and price dynamics, as well as the hedging of such volume and price sensitivities. For further illustration, we consider the case of renewable energy generation from wind power plants, but the methods shown can be transferred to other use cases, too.

3.1 Impact of Weather on Volume

First, to transform meteorological variables, particularly weather forecasts, into information relevant for energy companies, a series of conversions are required. This section aims to briefly illustrate how the impacts on energy systems can be calculated through the application of meteorological data and weather forecasts. In this context, we focus on the case where meteorological variables x are translated into energy company-relevant quantities E through simple functional relationships: $E = f(x)$. As such, the transfer function f could be physically or empirically derived and may be of any form. Note that in the example shown below, the function depends solely on one single meteorological variable. However, dependencies between different variables (for instance, wind direction for wind power) could be considered, too. For the consideration of more complex impact chains, such as the relationship between residual load and generation from renewable energy plants or the price sensitivity in the spot market to volume changes, see Section 3.2.

[6] Cf. Section 6.5 in https://www.ipcc.ch/report/ar6/wg3/chapter/chapter-6/
[7] Cf. https://cds.climate.copernicus.eu/datasets/sis-energy-derived-projections?tab=overview
[8] Cf. https://cds.climate.copernicus.eu/datasets/sis-extreme-indices-cmip6?tab=overview
[9] Cf. https://cds.climate.copernicus.eu/datasets/sis-heat-and-cold-spells?tab=overview
[10] Cf. https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels?tab=overview
[11] Cf. https://cdc.dwd.de/portal/
[12] Cf. https://www.ncei.noaa.gov/cdo-web/

Example: Power Curve of Wind Turbines

The variability in the power output of wind turbines is primarily influenced by local wind conditions, making wind a critical factor for energy providers. One of the greatest challenges and risks in integrating wind energy into the power grid is the complex and non-stationary structure of atmospheric wind fields, and thus the short-term variability of wind resources on time scales ranging from minutes to days. Models for generating (short-term) wind power forecasts generally require two categories of input data: Forecasts of wind speeds (and, if necessary, other relevant weather variables) at the wind farm location, typically derived from numerical weather prediction models and information about the wind farm, such as the technical characteristics of the installed turbines or the power curves of the turbines, which translate wind speed into electrical power. The relationship between wind speed and power output is illustrated in Figure 3 for the wind turbine type Enercon E126 7.5 MW and can be assumed to be analogous for other turbine types.

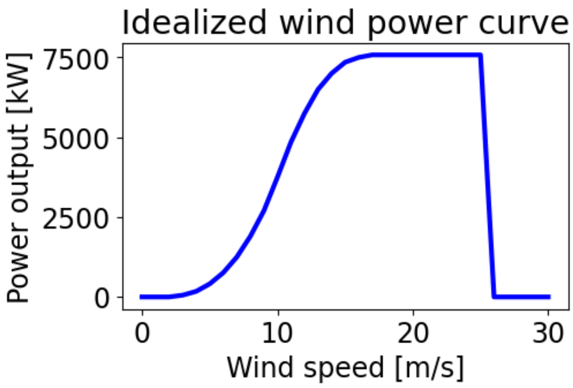


Figure 3: Shown is the profile of the power curve for a specific wind turbine type, which schematically represents the relationship between wind speed [m/s] and wind power generation [kW].

A speed of approximately 3 m/s can be referred to as the cut-in speed, which is the wind speed threshold at which the wind turbine begins generating electricity. Above 3 m/s, the curve follows a non-linear (i.e., cubic) progression until the maximum power output of the wind turbine is reached. To prevent damage to the rotor blades at very high wind speeds, the turbine shuts down at wind speeds above 25 m/s. If, for instance, ensemble forecasts of site-specific wind speeds at heights of 80 meters (i.e., at the height of a wind turbine's rotors) are converted into wind power generation using the power curve, the following result is obtained (see Figure 4). As can be clearly seen, there is significant uncertainty regarding the future wind power forecast at various points in time.

3.2 Impact of Weather on Prices

The weather-dependent fluctuations in renewable energy generation can directly impact the supply and demand balance, thereby causing significant volatility in spot prices on the electricity market. For example, when there is strong wind or high solar radiation, the electricity supply from renewable generation increases, which in turn leads to a decrease of spot prices. Conversely, during periods of low wind speed or low solar radiation, supply shortages may occur, leading to an increase of spot prices. As a result, there is a need for modeling price sensitivity (price risk) while considering generation uncertainty (volume risk). In the next subsection, we briefly discuss an approach which uses supply and demand curves[13] to model price sensitivity regarding volume uncertainty.

Example: Modeling of Prices Using Supply and Demand Curves

Here, we present an *ansatz* that can be used to estimate the probability and magnitude of price movements based on the Day-Ahead auction market data of EPEX Spot. The outlined approach is based on the work of Ziel and Steinert (2015), which demonstrate that it is possible to model electricity prices in a promising way by using such a method. It should be noted that in this report, only EPEX Spot market data from a few days is considered, as this section only aims to illustrate the application of the methodology. For a more detailed modeling, it would be necessary to create statistics from market data over several years. To introduce the model, it is helpful to first examine the EPEX Spot market and the bidding structure observed among its participants: on the EPEX Spot market, producers and consumers can submit bids for specific quantities.

Thereby, for each hour of the next day, the electricity supply from producers is balanced with the bids from consumers as part of the Day-Ahead auction conducted on the EPEX Spot market, such that the Market Clearing Price can be estimated from the intersection between the supply and demand curves. To better understand the process, let us now consider the following: first, to construct the supply curve, the quantities offered are sorted by price (i.e., from the lowest to the highest price), while for constructing the demand curve, the bid prices are ordered from the highest to the lowest price. The supply and demand curves are then formed by calculating the cumulative quantities for the respective bids. An example illustrating the supply and demand curves as well as their intersection from the aggregated supply and demand data of Spot for two selected hours is shown in Figure 5. It exemplifies for two selected hours of the day how the intersection of the two curves allows the estimation of both the traded volume (more precisely, the Market Clearing Volume) and the price (more precisely, the Market Clearing Price).

[13] Cf. X-Model by Ziel and Steinert (2015)

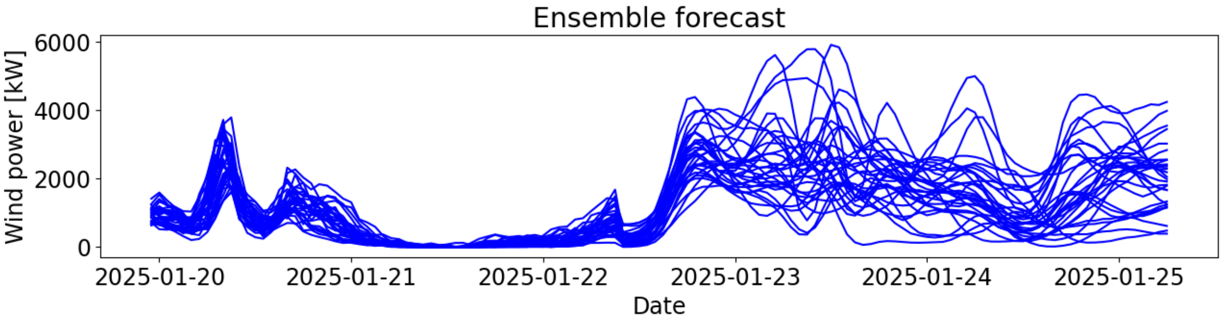


Figure 4: Shown are ensemble forecasts of wind power generation at a specific location.

Furthermore, it is clearly observable that the price at 6 p.m. on the selected day is significantly higher compared to 11 a.m. Looking more closely at the supply and demand curves, two typical phenomena can be identified. First, the traded volume at 6 p.m. is lower compared to 11 a.m., from which the price difference can be directly calculated. Secondly, the demand curve for each price and volume combination below the market price shows a steep negative slope (the opposite holds for the supply curve), which generally leads to the following conclusion: An increase in supply (i.e., a shift of the supply curve to the right), for example, through higher generation from renewable energy sources, would lead to an overall lower price level (cf. Merit-Order Model[14]).
Considering the previously mentioned phenomena, a basic approach for determining potential price sensitivities due to volume changes can be derived through the modeling (or forecasting) of supply and demand curves using the following data: historical supply and demand curves from EPEX Spot, historical time series of market clearing volume and market clearing prices, and historical Day-Ahead forecasts for renewable energy generation (since the generation from renewable energy sources can have a strong influence on the spot price, particularly due to the merit-order effect on the volume of bids at lower prices). Then, the following steps are used to create a forecast for the supply and demand curves and, through their intersection, estimate the price. Due to the high number of possible bids, the bid volumes are first divided into a limited number of (uniform) volume classes to keep computational effort as low as possible, from which price classes are then derived. In the next step, these are forecasted using a stochastic model and then used to reconstruct the supply and demand curves, which ultimately serve to estimate the price from their intersection.

Investigation of Price Sensitivity Due to Volume Changes

In the previous sections, the methodology of a model that can be used to make price forecasts based on supply and demand curves was outlined. The prediction of the latter is modeled using a regression approach, where the relevant variables include the Market Clearing Prices and Volumes from previous auctions, the predicted power generation from conventional power plants, and the predicted generation from solar and wind energy in the Day-Ahead market. However, the predicted generation amount in the Day-Ahead can have significant forecast errors. In the Intraday market, deviations from the reported schedules are typically balanced out. As a result, costs are composed of the product of the short-term traded quantity (i.e., the volume deviation) and the price difference between the Intraday price and the Day-Ahead price. Since the Intraday price is primarily determined by the sum of all expected schedule deviations (i.e., the uncertainty in generation from renewable energy plants), higher positive (or negative) price differences arise with increasing demand (or supply) in the Intraday market, meaning the balancing of positive (or negative) forecast errors. In this section, an approach to investigate price sensitivity due to generation uncertainties will be presented, based on the previously described methodology and results. It should be noted that, without loss of generality, some assumptions will be made for simplification purposes, as the goal here is to only illustrate the methodology. We now assume that, using the model described in the previous sections, a forecast for the supply and demand curves for a specific hour on the next day has been made. Next, probabilistic forecasts are generated, which, instead of providing a point forecast, offer an estimate of the price sensitivity with respect to volume uncertainties. Since we are particularly interested in the impact of weather forecast uncertainties and the resulting fluctuations in electricity generation from renewable energy sources, as well as their effect on (Intraday) prices, the demand curve is assumed to remain constant, and only the effects of a probabilistic forecast on the supply curve are modeled.
Furthermore, for simplified representation, it is assumed that a simple shift of the supply curve to the right (or left) occurs when a higher (or lower) amount of renewable energy is generated, and the price sensitivity can be directly derived from the corresponding shift of the intersection point.

[14] e.g., https://www.next-kraftwerke.de/wissen/merit-order

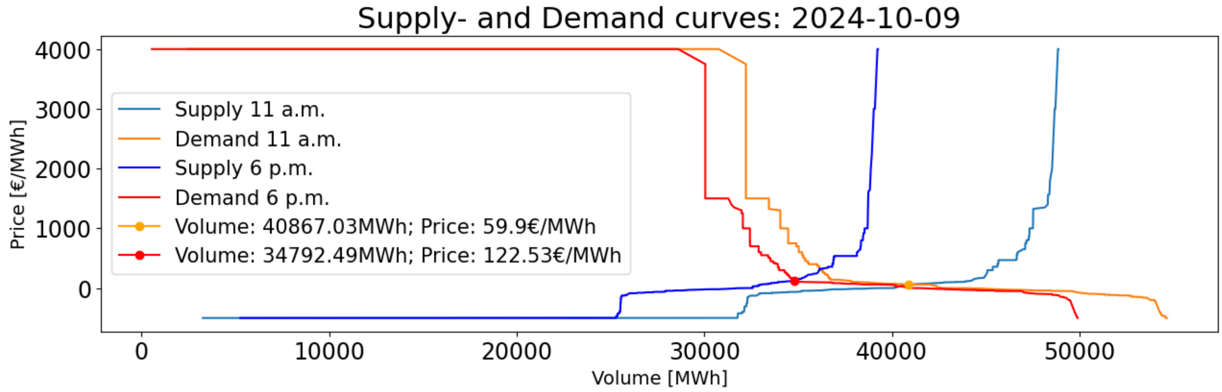


Figure 5: The supply (light and dark blue) and demand curves (orange and red) for two different times on a selected day, as well as their intersection points and the corresponding market clearing volumes and prices, are shown.

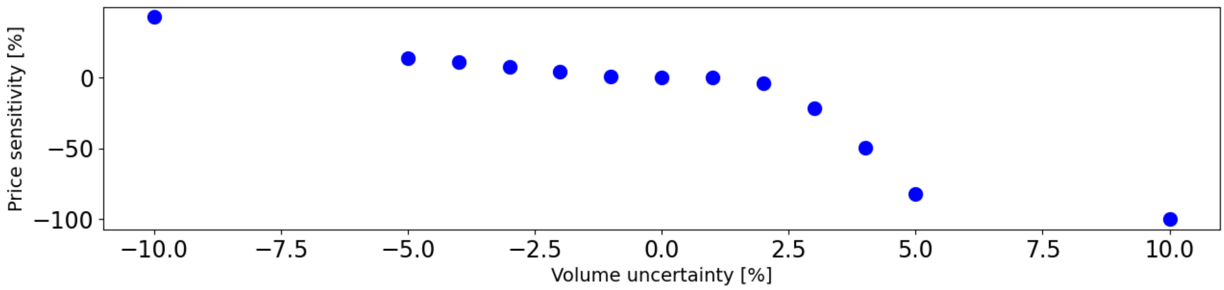


Figure 6: The relationship between percentage price and volume change is shown, which results from the shift of the supply curve for a specific time and day.

Figure 6 further illustrates the relationship between price sensitivity and volume uncertainty for volume changes of up to $\pm 10\%$ for a selected hour on a given day[15], clearly showing, as expected, a negative (non-linear) dependency. In this case, a volume uncertainty of $\pm 1\%$ would result in an (asymmetric) price sensitivity of approximately -1% or $+5\%$.

3.3 Hedging of Volume/Price Sensitivity

Uncertainties in price and volume forecasts can pose a non-negligible risk for energy companies. In this section we introduce an approach which aims to identify the optimal hedge volume in the Day-Ahead market auction for an upstream renewable pay-as-produced power purchase agreement (PPA), taking into account uncertainties in weather forecasts. In particular, ensemble forecasts and the risk regarding exposure against market prices are taken into account, i.e., we use the general concept of the delta position, which is defined as the sensitivity of the value of a portfolio V (or a PPA) at a specific time against a market price change ($\delta = \partial V / \partial p$) and indicates the required volume for an effective hedge against changing market prices.

As an example, let us consider the electricity generation volume at a (renewable) power plant, where the risk-optimal hedging volume for the Day-Ahead auction is to be calculated. Instead of relying on a single (expected) forecast path for the generation volume (described in this section as *naive* approach), we assume that ensemble forecasts for the generation volume of the next day are available. Moreover, we model the price sensitivity to changes in the generation volume using the supply and demand curves as shown in Section 3.2. Then, this is used to determine the distribution of cash flows, i.e., the P&L distribution of the PPA, and to derive for each ensemble path the respective delta position. Exemplifying this, we analyze results for a wind park (for a specific hour), i.e.,

- δ_{naive}: The mean of the predicted generation quantity for all ensemble paths at the selected hour in the Day-Ahead market is hedged.
- $\delta_{50\%Quantile}$: The quantity corresponding to the 50% quantile (median) of the distribution of the calculated δ is hedged.

For the case under consideration, we observe that the hedging strategy $\delta_{50\%Quantile}$ indicates a smaller volume compared to δ_{naive} (cf. δ in Table 1). Moreover, for a comparison of the efficiency of the hedging strategies, we compare the results for calculated statistics of the corresponding P&L distributions, which point out that the

[15] The dependency function is highly variable on an hourly basis and should subsequently be adjusted dynamically.

Table 1: Numerical results of P&L statistics for considered hedging strategies.

Hedging Strategy	δ	Mean	Std. Deviation	1% Quantile
δ_{naive}	2.45	271.46	214.32	-34.19
$\delta_{50\%Quantile}$	1.86	288.07	216.87	50.12

strategy $\delta_{50\%Quantile}$ yields a higher average result (compared to δ_{naive}) in this specific case. In addition, the strategy $\delta_{50\%Quantile}$ shows no negative value for the 1% quantile of the P&L distribution (i.e., extreme losses) and exhibits a comparably low variance. In summary, the results show that it could make sense to initially trade a lower volume (i.e., consider a *risk-optimal* hedging strategy) than the expected forecast in the Day-Ahead auction, thus reducing the risk of a possible loss that could arise due to forecast errors.

4 Summary

We provided an overview of methods for the quantification of weather risk for energy companies. First, weather data and the forecasts of numerical weather models were discussed, and it was shown how these can be used to monitor and quantify weather-related opportunities and risks. In particular, the use of ensemble forecasts (as opposed to individual, expected forecast paths) represents a promising option for monitoring and ultimately managing weather risks more accurately. In addition, a conceptual methodology was presented that allows to quantify price sensitivities due to volume uncertainties resulting from fluctuations in the weather forecast and a concept for determining the risk-optimal hedge volume was presented. The latter approach is able to provide a relevant hedging strategy using ensemble forecasts as input and takes price sensitivities due to volume uncertainties into account. First results obtained for a simple, conceptional test case are promising and provide confidence that a detailed implementation and application of the model would offer an added value for energy companies. Nevertheless, for a more precise determination of a risk-optimized strategy, more detailed analyses and backtesting of the methodology with measured/realized data should be conducted.

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