REVIEW OF WIND FUTURES BY GAUSSIAN AND LÉVY JUMP RISKS

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Abstract

Wind power futures, once a hedging tool in energy-related derivatives markets were discontinued due to low liquidity. However, recent increases in electricity price spreads have introduced new financing challenges for renewable energy projects in Europe, leading to heightened price risks and a renewed demand for such instruments. Also, the regulation on renewable electricity for renewable fuels of non-biological origin (RFNBO) — compliant hydrogen production poses a supply uncertainty risk to hydrogen developers. As both such project developers seek ways to mitigate these risks, this paper reviews the existing literature on modelling strategies for hedging wind power production risks. The review, based upon a structured literature review following vom Brocke et al. (2009), provides a comprehensive overview of arbitrage models incorporating seasonal elements and stochastic jump risks, as well as equilibrium pricing models. The variations and conclusions of these models are analyzed in the context of the altered market conditions in 2024. This analysis offers insights into the applicability of current models for pricing risk premia and identifies gaps under the evolving market realities.

Keywords: Wind Power, Futures, Hedging, Risk Premium, Gaussian Risk, Lévy Process

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1. INTRODUCTION

Risk management is one of the central elements of every company, project, or profit-oriented entity. In the context of the steadily increasing renewable power generation and more specifically wind power generation, the weather-induced risks are getting increasing attention (Kamani & Ardehali, 2023; Masala et al., 2022). In the case of a wind farm, the major production parameter is the wind speed or the wind volume, where initial works for modelling the risk premium have been done (Freudmann, 2011; Bessembinder & Lemmon, 2002; Ehrhardt, 2002; Benth & Benth, 2009; Benth et al., 2008; Benth & Pircalabu, 2018; Härdle et al., 2021). Unfortunately, this parameter can neither be influenced nor controlled and thus poses an uncontrollable risk element for the wind power producer in realizing the project financing (Thomaidis et al., 2023; Erfani & Tavakolan, 2023).

Coinciding with the German tariff system shift, which changed to an auction model, awarding contracts to the cheapest bids up to a set capacity threshold, the National Association of Securities Dealers Automated Quotation (NASDAQ) and European Energy Exchange (EEX) introduced hedging tools for wind power, with EEX launching "Energiewende Products" in 2016 (discontinued in 2020) and NASDAQ offering wind power futures in 2015 (delisted in 2023). These derivatives aimed to mitigate wind volume risk but had low liquidity, leading to their removal. In light of the increasing spreads in the European power markets in 2023 and 2024, with German power markets experiencing more than 300 hours with negative prices in 2023, and more than 300 hours in 2024 until the end of July, a drastic up from around 70 hours in 2022, the challenges onto the financing of wind power projects increased by the risk in power sales prices.

Even though the wind power futures were delisted just before the electricity price spread took off, the wind power developers are now eager to derisk their developments more than ever. On top, the Delegation Regulation (European Union, 2023) enforces the need for temporal and geographical correlation in conjunction with the additionality requirement on renewable electricity and a direct link between the electricity producer and the hydrogen producer for the production of renewable fuels of non-biological origin (RFNBO) — compliant hydrogen from 2028 onwards, poses supply uncertainty risk on hydrogen developers (Talus et al., 2024). So, this group of developers as well is now seeking ways to derisk their electricity volume risk. To shed some light onto past derived models, we aim to compile an overview of past models and compare the existing works with respect to their applicability under the changed market conditions since pre-2021. The objective is to outline the need for an adaptation of the existing models and to stimulate the relaunch of either over-the-counter (OTC) or new wind futures products with adapted associated risk models. We, therefore, will answer the following research questions:

RQ1: What models exist to model the volume risk for wind power, which have been reflected via wind power futures in the past?

RQ2: How do these models differentiate in their findings?

RQ3: How do the recent changes in market spreads reflect within these models and what adaptations are required to include these market changes in the models?

The paper is structured as follows. Section 2 shows our applied methodology of a structured literature review to compile an overview of existing literature on wind power futures. Thereby we identified exclusively pre-2021 works. Sections 3 and 4 discuss the two main modelling techniques identified, the no-arbitrage pricing model and the equilibrium pricing model. Section 5 discusses the findings from existing models and brings these models in the context of changed market conditions observed in 2024 compared to pre-2021 wind markets. Finally, Section 6 summarizes the findings and provides an outlook on the identified gaps.

2. LITERATURE REVIEW

To become familiar with existing findings on the modelling of wind power futures a structured literature review following vom Brocke et al. (2009) formed the basis. The overall focus is to identify research outcomes and models reflecting wind power production in light of weather uncertainties. Following Cooper (1988), the search can be clustered as follows. The objective is to identify previously discussed ideas and strategies. To ensure broad coverage, the search extends to general weather risks and wind financing in addition to wind power futures. The methodological approach will categorize and combine relevant models while excluding those not applicable to wind-related weather risks. These groups of strategies will then be linked to specific examples and discussed. A neutral stance will be maintained throughout. The outcome will serve as a summary of models for future researchers, experts, and businesses, providing a representative overview. Complete coverage is not the aim, nor is it practically achievable given the wide scope of risk and weather models.

With two step forward and backward search, we were able to identify seven key literature models: Benth and Benth (2009), Benth and Pircalabu (2018), Alexandridis and Zapranis (2013), Melzer et al. (2017), Hees (2021), Gersema and Wozabal (2017) and Härdle et al. (2021). They cluster into jump risk and game equilibrium pricing models.

Among the jump risk models, most models build upon initial works by Benth et al. (2007) on weather derivatives on temperature. While temperature is of less criticality for wind production, the methodology still holds. Benth et al. (2007) separated the power production risks into a seasonal component and a stochastic component. Subsequent literature uses these jump-diffusion models to reflect wind speeds (Benth & Benth, 2009; Benth & Pircalabu, 2018; Alexandridis & Zapranis, 2013; Melzer et al., 2017; Hees, 2021; Härdle et al., 2021). In light of the challenge to correctly reflect an autocorrelation between the model and reality, the frameworks use a combination of intraday and spatial modelling, comparing a Gaussian candidate model with non-Gaussian alternatives using information criteria and model assumption checks (Härdle et al., 2021). Following Benth et al. (2007), the models thereby combine a long-term seasonal effect with a short-term stochastic effect.

A different approach emerges from equilibrium models. For this Gersema and Wozabal (2017) introduce a two-player game consisting of the owners of wind power plants and the owners of conventional generation plants. They relate the hedging strategies of both players to mitigate their respective risks.

3. REVIEW OF NO-ARBITRAGE PRICING MODELS

The models discussed in this section, by Benth and Benth (2009), Benth and Pircalabu (2018), Alexandridis and Zapranis (2013), Melzer et al. (2017), and Hees (2021) share a common underlying method based on a no-arbitrage pricing model. This model establishes a risk-neutral probability measure and links it with a market price of risk. However, it does not account for the mechanics and interaction with the position holder's business model, leaving risk premia unexplained. Consequently, the risk premium is inferred as the disparity between actual and calculated prices.

The models thereby, except from Hees (2021), consist of a composition of a seasonal effect Λ_t plus a stochastic short-term variation component X_t.

$$\widehat{U}_t = X_t + \Lambda_t \tag{1}$$

The stochastic short-term variation component X_t is thereby modelled either by a Gaussian risk factor approach or via a Lévy process with jumps. This stochastic portion is detailed in subection 3.3. The seasonal effect is discussed in subection 3.2. The pricing of the futures then follows the respective wind power futures contractual definition with the risk-neutral expectation of the underlying index, which is normally the wind production.

3.1. Underlying index and data for modelling

The models published rely on several sources for the raw data. These sources reflect the respective wind power futures the individual publications are referring to and discussing.

Benth and Benth (2009) focus on the sole existing wind power future at the time of writing, the US Futures Exchange wind power futures. They utilize wind speed data averaged over New York State Region I, sampled every three hours. This data was aggregated to a daily average, corrected for leap years, covering January 1, 1987, to December 31, 2011. References are made to New York State Regions II and III, showing similar results. The wind speed is regarded as the primary factor for wind power production, akin to a wind production index, though this terminology emerged post-publication. Thus, for simplification, the wind speed data described is treated as a wind production index.

Melzer et al. (2017) base their analysis on the NASDAQ wind power futures for the German market. For the raw data of their model, the starting points are realized wind power production and installed capacity values as provided by the German transmission system operators, which are used to derive the wind power utilization U_t, as also used in the actual wind power index.

$$U_t = \frac{W_t}{C_t} 100 \tag{2}$$

where, W_t is the wind power production at time t, C_t is the installed wind power capacity at time t, and the time index t. The raw data yield comparable data from 2010 until 2016, corrected for leap years, and the reported quarterly hour raw data is averaged for daily values following the pricing schemes.

Benth and Pircalabu (2018) focus on NASDAQ wind power futures for Germany, briefly mentioning EEX-based futures without elaboration. They compare NASDAQ data with a synthetic wind power production index from MeteoGroup, also underlying NASDAQ wind power futures, spanning 37 years from January 1, 1979, to December 31, 2015. It is equivalent to the index for wind power utilization U_t as in Eq. (1) and (2) but relies on different source data and thus is expected to yield different values.

As stated earlier, Hees (2021) is proposing a theoretical model without direct application of a wind power future on the market. As such, this publication is not using any source data for quantitative data analysis.

3.2. Seasonal effect

When analyzing the source data for the models, irrespective of wind speed data or wind power utilization, all publications observe a seasonal effect Λ_t, which is one element in the description of the wind power utilization function.

While Benth and Benth (2009), Benth and Pircalabu (2018) and Melzer et al. (2017) calculate an explicit seasonal effect by means of the below-mentioned techniques, Hees (2021) limits its discussion on seasonality to the existence of a seasonal effect within the underlying volatility and jump intensity functions, which is not directly modelled. Out of the above publications, Melzer et al. (2017) is the only one to apply multiple seasonality calculation methods and to compare them with regard to the best fit.

3.2.1. Seasonality modelling of the underlying index

Various techniques from existing literature are available for modelling the underlying index function, as adapted in related publications. These include truncated Fourier series (TFS), local linear smoothing (LLS), and periodic B-splines regressions.

Truncated Fourier series

The TFS in terms of a seasonal component is a Fourier-like expansion of cosine parameters weighted by phase and scaling factors. In terms of seasonality, it is generically defined as:

$$\Lambda_t = c_0 + c_1 t + \sum_{l=1}^{L} d_l \cos\left(\frac{2\pi(t - e_l)}{l \times 365}\right) \tag{3}$$

where, c_0 and c_1 represent parameters, more specifically c_0 representing the intercept, c_1 representing the linear trend, and d_l and e_l represent seasonality parameters. $l = 1, \ldots, L$ defines the separate Fourier elements (Melzer et al., 2017).

Benth and Benth (2009) employ a simplified case using sine and cosine functions to capture yearly and half-yearly effects.

$$\Lambda_t = c_0 + d_1 \cos\left(\frac{2\pi}{365}t\right) + d_2 \sin\left(\frac{2\pi}{365}t\right) + d_3 \cos\left(\frac{4\pi}{365}t\right) + d_4 \sin\left(\frac{4\pi}{365}t\right) \quad (4)$$

where, d_1, d_2, d_3, and d_4 represent weighting seasonality parameters. Benth and Pircalabu (2018) simplify this approach further by considering yearly effects only.

$$\Lambda_t = c_0 + d_1 \sin\left(\frac{2\pi}{365}t\right) + d_2 \cos\left(\frac{2\pi}{365}t\right) \quad (5)$$

The TFS can be considered as the method of choice among the different techniques presented due to its simplicity, and good fit in direct comparison (Melzer et al., 2017).

Local linear smoothing

Local linear regression as used by Melzer et al. (2017) is the estimation of a best-fit regression line over the respective data points. For the LLS, this methodology is complemented by a kernel, which is a window function of points to be considered for each step. It is computed by solving a weighted least square problem:

$$\Lambda_t = \underset{e,f}{argmin} \sum_{t=1}^{365} \{\bar{U}_t - f_{1s} - f_{2s}(t-s)\}^2 K\left(\frac{t-s}{h}\right) \quad (6)$$

where, $\bar{U}_t$ represents the daily average wind power utilization over the years, f is a parameter for the local linear regression and $K\left(\frac{t-s}{h}\right)$ is a kernel to evaluate the squared deviation from the local linear regression.

The resulting function is smooth and performs well for large bandwidths, as smaller bandwidths tend to pick up noise from the stochastic portion (Melzer et al., 2017).

Periodic B-spline regression

The basis spline curve is a piecewise polynomial function with local control points connected at knots. This allows for each segment to be formulated using simple polynomial functions. These polynomials are adjusted to ensure differentiability at the knots and adherence to input control points. Being a local form, changes in points within a segment interval affect only that segment. In the periodic case, the last and first knots are linked to create a periodic form. This periodic form, reflecting seasonality, is referred to as:

$$\Lambda_t = \underset{\alpha_j}{argmin} \sum_{t=1}^{365} \left\{\bar{U}_t - \sum_{j=1}^{J} \delta_j \Psi_j(s_t)\right\}^2 \quad (7)$$

where, $\bar{U}_t$ represents the daily average wind power utilization over the years, $\Psi_j(s_t)$ is a vector of known basis function, δ_j are coefficients, and j is the number of knots.

All in all, the periodic B-spline regression shows a good fit to the seasonality component for a suitable selection of knots (Melzer et al., 2017).

3.2.2. Seasonal variance modelling

In addition to modelling the seasonality of the underlying index, addressing seasonal variance is crucial. While Benth and Benth (2009) contend that residuals of the seasonality-corrected index reveal no further seasonality, only the squared residuals do, and they address this using a TFS method. On the other hand, Melzer et al. (2017) introduce smooth inter-expectile range (sIER) and smooth inter-quartile range (sIQR) methods for modelling seasonal variance.

Truncated Fourier series

Similar to in Eq. (3), the TFS in terms of a seasonal variance for the squared residual is given as:

$$\sigma_t^2 = c_{\sigma,0} + \sum_{l_\sigma=1}^{L_\sigma} d_{\sigma,l} \cos\left(\frac{2l_\sigma \pi}{365}t\right) \quad (8)$$

with $c_{\sigma,0}$ and $d_{\sigma,l}$ representing parameters, more specifically $c_{\sigma,0}$ representing the intercept, and $d_{\sigma,l}$ seasonality parameters for the separate Fourier elements $l_\sigma = 1, \dots, L_\sigma$. Benth and Benth (2009) use $L_\sigma = 3$.

Smooth inter-expectile range

The sIER is a measure of the tail variation. It coincides with the volatility for alpha levels of 0, 0.25 and 0.75 and defines the ratio of data points which should be below the respective anticipated level for the given alpha level. It gives a measure for the volatility at specific alpha levels considering the distance of the data points above and below the chosen alpha levels. Its loss function is defined as:

$$\rho_\alpha = |\alpha - I\{u < 0\}||u|^2 \quad (9)$$

which is an alpha level moment measure, that is equivalent to the mean for an alpha level of 0.5. The expectiles for alpha levels beside 0.5 are defined by means of an arbitrary local model $Y_t = \theta + \varepsilon_t$ as $e(\alpha, \varepsilon) = argmin_\theta \mathrm{E}_{\rho_\alpha}[Y_t - \theta | \mathrm{F}_t]$. For the normalized seasonal sIER, this relates to the definition as:

$$\sigma = \frac{e(\tau = 0.75|X) - e(\tau = 0.25|X)}{2e^{-1}(\tau = 0.75|\Phi)} \quad (10)$$

In order to achieve a smooth fit, smoothing splines are applied with truncated power basis functions, knots at every observation point and a roughness penalty approach (Melzer et al., 2017).

Smooth inter-quartile range

The sIQR considers half of the data points only, namely the points lying in the centre two quartiles and ignores the lower and upper quartiles. By that, outliers are not considered. Its loss function is defined as:

$$\rho_\alpha = |\alpha - I\{u < 0\}||u| \quad (11)$$

which is the alpha quantile. Here again, the probability measure at alpha level 0.5 corresponds to the median.

Similar to the sIER, the normalized seasonal sIQR is defined as:

$$\sigma = \frac{med(|Y - med(Y)|)}{2\Phi^{-1}(\alpha = 0.75)} \quad (12)$$

with respective smoothing splines and truncated power basis functions.

3.3. Stochastic short-term variation using Gaussian risk factors

For the modelling of the stochastic short-term variation component x_t, an Ornstein-Uhlenbeck stochastic process with Gaussian risk factors can be applied. This demands symmetric data. The subsequent Gaussian risk factor approach, which follows the Jacobi process, benefits from a simple expression for the future price, which can be explicit. On the other hand, the model parameter estimation is challenging (Melzer et al., 2017).

3.3.1. Symmetrization of data

Contrary to the symmetric data demand, the source data on wind power utilization and wind speeds reveal a skewed distribution. A data symetrification is thus required (Benth et al., 2008; Melzer et al., 2017). Following a standard log transformation is problematic in light of a missing rationale (Benth et al., 2008; Benth & Benth, 2009) and due to the narrow band of the source data increasing the likelihood of autocorrelation artefacts (Melzer et al., 2017). A better option is arguably a Box-Cox transformation, which yields (Benth et al., 2008; Benth & Benth, 2009):

$$\hat{U}_t = \begin{cases} \dfrac{{U_t}^{\lambda} - 1}{\lambda}, \lambda \neq 0 \\ \ln(U_t), \lambda = 0 \end{cases} \quad (13)$$

for $\hat{U}_t$ as the Box-Cox transformed data and λ as the tunable Box-Cox transformation parameter.

An alternative is a logit transformation given by Melzer et al. (2017):

$$\hat{U}_t = log\left(\frac{U_t}{1 - U_t}\right) \quad (14)$$

3.3.2. Ornstein-Uhlenbeck stochastic process

The Ornstein-Uhlenbeck stochastic process with Gaussian risk factors is introduced by Benth and Benth (2009) in the vector form:

$$dX_t = \overleftrightarrow{A} X_t dt + e_p \sigma_t dB_t \quad (15)$$

where, X_t is the state vector, e_p is the p'th unit vector[1], σ_t is the standard deviation of the residual at time t, which can be expressed as the seasonal variance following Eq. (8), (10) and (12), B_t is a standard Brownian motion and $\overleftrightarrow{A}$ is a $p \times p$ matrix with:

$$\overleftrightarrow{A} = \begin{bmatrix} 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & \dots & 1 \\ -\alpha_p & -\alpha_{p-1} & -\alpha_{p-2} & \dots & -\alpha_1 \end{bmatrix} \quad (16)$$

where, α_p, $\alpha_{p-1}, \alpha_{p-2}$, and α_1 are constants.

By means of the Itô formula (Karatzas & Shreve, 1991), this leads to:

$$X_s = exp\left(\overleftrightarrow{A}(s - t)\right) X_t + \\ + \int_t^s exp\ (\overleftrightarrow{A}(s - u))\, e_p \sigma_u dB_u \quad (17)$$

for the time $0 \leq t \leq s \leq T$, with T being the upper limit of the data source.

Under consideration of a risk premium θ, Eq. (15) and (17) are rewritten as:

$$dX_t = \left(\overleftrightarrow{A} X_t + e_p \sigma_t \theta_t\right) dt + e_p \sigma_t dB_t^\theta \quad (18)$$

$$X_s = exp\big(A(s - t)\big) X_t + \\ + \int_t^s exp\left(\overleftrightarrow{A}(s - u)\right) e_p \sigma_u \theta_u du + \\ + \int_t^s exp\ (\overleftrightarrow{A}(s - u))\, e_p \sigma_u dB_u^\theta \quad (19)$$

where, $B_t^\theta = B_t - \int_0^T \theta_s ds$ is the Esscher transform and relates to the risk premium θ under the assumption of θ_s being a square-integrable function with the integral from 0 to T being a real value (Benth et al., 2008; Melzer et al., 2017).

The corresponding mean is:

$$\mu_\theta(t, s, X_s) = e_1^\intercal exp\left(\overleftrightarrow{A}(s - t)\right) X_t + \\ + \int_t^s e_1^\intercal exp\left(\overleftrightarrow{A}(s - u)\right) e_p \sigma_u \theta_u du \quad (20)$$

and its variance

$$\Sigma^2(t, s) = \int_t^s \sigma_u^2 \left(e_1^\intercal exp\left(\overleftrightarrow{A}(s - u)\right) e_p\right)^2 du \quad (21)$$

For further simplification, a continuous-time autoregressive (CAR(4))-model based on a fourth-order autoregressive model (AR(4)) was identified as a suitable fit for the deseasonalized wind speed data representation (Benth et al., 2008; Benth & Benth, 2009).

When applying a Logit transformation as then the process is given by the inverse transformation combination of the seasonal effect Λ_t as well as the derived values from Eq. (20) and (21) as:

[1] The p'th unit vector is given as: $e = \begin{bmatrix} 0 \\ \dots \\ 0 \\ 1 \end{bmatrix}$.

$$U_t = \frac{1}{1 + exp\,(-\Lambda_t - \mu_\theta(t,s,X_t) - \Sigma^2(t,s)Z)} \quad (22)$$

with Z being white noise. The special case of a log transfer yields (Benth & Benth, 2009):

$$U_t = \begin{cases} (\lambda(\Lambda_t + \mu_\theta(t,s,X_t) + \Sigma^2(t,s)Z) + 1)^{\frac{1}{\lambda}}, \\ \lambda \neq 0 \\ \Lambda_t exp\,(X_{1t}), \\ \lambda = 0 \end{cases} \quad (23)$$

3.3.3. Wind power future pricing

As per the definition of the wind power future, for all, the US Futures Exchange, the NASDAQ and the EEX wind power futures, the futures are settled against the actual performance of a defined index for the period from τ_1 to τ_2 and will be financially settled at the time τ_2. The price for the future F_{t,τ_1,τ_2} at time t for the period from τ_1 to τ_2 is as such assumed as the expectation value E_Q of a risk-neutral probability Q.

$$F_{t,\tau_1,\tau_2} := E_Q[U_{\tau_1,\tau_2}|\mathcal{F}_t] \quad (24)$$

where, $\mathcal{F}_t$ is a filtration comprising all information up to time t and U_{τ_1,τ_2} is the underlying index from a period τ_1 to τ_2 (Benth & Benth, 2009).

Applying the beforementioned formulations for seasonal correction and Gaussian risk modelling (Benth & Benth, 2009), the US Futures Exchange price is stated as:

$$F_{t,\tau_1,\tau_2} = \begin{cases} \overline{W}_{\tau_1,\tau_2} + M_{1/\lambda}\left(\lambda\left(\Lambda_t + \mu_\theta(t,s,X_t)\right) + 1,\ \lambda^2\Sigma^2(t,s)\right), \lambda \neq 0 \\ \overline{W}_{\tau_1,\tau_2} + \sum_{\tau_1}^{\tau_2} exp\left(\Lambda_t + \mu_\theta(t,s,X_t) + \frac{1}{2}\Sigma^2(t,s)\right), \lambda = 0 \end{cases} \quad (25)$$

with $\overline{W}_{\tau_1,\tau_2}$ being the summed daily wind speeds during the time period from τ_1 to τ_2 subtracted from 100 to reflect the underlying index. $M_z(x,y)$ is z'th moment of a normal random variable with mean x and variance y^2, which is already depicted in Eq. (25) by the corresponding values.

Melzer et al. (2017) adapt the wind power futures price to the NASDAQ-based futures, where the prices are determined by the average wind power utilization within the future's contract period as:

$$F_{t,\tau_1,\tau_2} = \frac{1}{\tau_2 - \tau_1}\int_{\tau_1}^{\tau_2}\left(1 + exp\left(-\Lambda_t - \mu_\theta(t,s,X_t) - \frac{1}{2}\Sigma^2(t,s)\right)\right)^{-1} \quad (26)$$

3.3.4. Risk premium

The modelling approach using no-arbitrage pricing does not incorporate a strategic element for the risk premium directly. It is possible to have a risk premium factor θ included to reflect an explicit term for risk premia. Under no-arbitrage pricing models, this risk premium is derived analytically as the difference between observed and modelled values (Gersema & Wozabal, 2017; Benth & Benth, 2009):

$$R_{t,\tau_1,\tau_2} = F^Q_{t,\tau_1,\tau_2} - F^P_{t,\tau_1,\tau_2} \quad (27)$$

3.4. Stochastic short-term variation using Lévy process type jump risks

An alternative method is a Lévy process-based jump risk. Unlike the Gaussian risk approach, the state vector x_t results from the uncorrected wind power utilization $U_t = X_t + \Lambda_t$, as symmetry is not a base requirement for this approach. The Lévy process approach has the advantage over the Brownian motion approach or a Jacobi process in that the model parameter estimation is straightforward and the marginal distribution is fixed to the beta distribution (Melzer et al., 2017).

The Ornstein-Uhlenbeck stochastic process follows the approach analogous (Melzer et al., 2017):

$$dX_t = \overleftrightarrow{A}X_t dt + e_p dL_t \quad (28)$$

where, e_p is the p'th unit vector and $\overleftrightarrow{A}$ is a $p \times p$ matrix following Eq. (16) with adapted constants $\alpha_{p..1}$.

The Lévy process L_t can therein be represented as:

$$L_t = \int_0^t \int_0^\infty zN^L\, ds\, dz \quad (29)$$

where, t is defined to be a time between 0 and T, and N^L is a Poisson random measure (PRM) with l as a Lévy measure that fulfils $\int_0^\infty zldz < \infty$. The integral from zero to infinity thereby dictates the jump amplitudes and can be limited to a desired range on the interval from zero to infinity.

Under the assumption that all eigenvalues of the matrix $\overleftrightarrow{A}$ have a negative real part of a stationary solution (Melzer et al., 2017):

$$X_t = \int_{-\infty}^t exp\left(\overleftrightarrow{A}(t-s)\right) e_p dL_s \quad (30)$$

The above can be further expressed as a CARMA(p,q) — continuous-autoregressive-moving-average process without stochastic volatility by Melzer et al. (2017):

$$Y_t = \int_{-\infty}^t b^T exp\left(\overleftrightarrow{A}(t-s)\right) e_p dL^s \quad (31)$$

with the state equality $Y_t = b^{\intercal} X_t$, X_t being the stationary solution. Y_t is the stochastic short-term part in the uncorrected wind power utilization $U_t = Y_t + \Lambda_t$ and a vector b of p-length[2].

The wind power utilization index results from the CARMA*(p,q)* solution Y_t from plus the seasonal effect Λ_t:

$$U_t = \Lambda_t + \int_{-\infty}^{t} b^T exp\left(\overleftrightarrow{A}(t-s)\right) e_p dL_s \quad (32)$$

The wind power futures price now yields (Melzer et al., 2017):

$$F_{t,T} = \begin{matrix} \Lambda_T + \int_{-\infty}^{t} b^T\, exp\left(\overleftrightarrow{A}(T-s)\right) dL_s + \\ +E_Q(L_1)\int_{t}^{T} b^T exp\left(\overleftrightarrow{A}(T-s)\right)\theta_s ds \end{matrix} \quad (33)$$

for a future at time t with delivery at time T, with $0 < t < T$.

3.4.1. Representation with scaling term in linear form

The approach via a Lévy process can also be modified including a linear scaling constant μ for the stochastic function portion, and by a linear approach. Composing the wind power production index in an exponential and multiplication form produces (Benth & Pircalabu, 2018).

$$U_t = \Lambda_t exp\,(-X_t) \quad (34)$$

This modifies Eq. (28) to:

$$dX_t = A(\mu - X_t)dt + dL_t \quad (35)$$

Under same assumptions as above, the solution from Eq. (30) then is rewritten to:

$$X_t = \mu + \int_{-\infty}^{t} exp\,(A(t-s))\, dL_s \quad (36)$$

where, the scaling term μ is chosen to reflect the upper and lower limits by:

$$max(\Lambda_t)\, exp(-\mu) = 1 \xrightarrow{yields} \mu = ln\,(max(\Lambda_t)) \quad (37)$$

The underlying wind power utilization index is again the conjecture of the solution X_t from Eq. (36) plus the seasonal effect Λ_t the corresponding wind power future price reads (Benth & Pircalabu, 2018):

$$F_{t,T} = \Lambda_T + exp(-\mu(1 - exp(-A(T-t))) \times \times \left(\frac{\kappa - \theta + exp\,(-A(T-t)}{\kappa - \theta + 1}\right)^{\frac{\lambda_\kappa}{A(\kappa-\lambda)}} \quad (38)$$

3.4.2. Representation with multiple zero-reverting Ornstein-Uhlenbeck processes

Hees (2021) approaches the wind power production index modelling by a stochastic process Y_t alone without a direct seasonal component:

$$Y_t = \mu_t + \sum_{k=1}^{n} a_k X_{k,t} \quad (39)$$

here, a_k are weights for the respective processes $X_{k,t}$ and μ_t is a continuous real-valued deterministic function, which defines the floor value of the process Y_t. (Hees, 2021) suggests to represent $\mu_t := a\, sin(bt + \varphi) + \delta$, where a, b, φ and δ are chosen constants to yield a floor value function with varying amplitude, which should be close to zero.

This adapts Eq. (28) to:

$$dX_{k,t} = -\lambda_k X_{k,t} dt + \sigma_{k,t} dL_{k,t} \quad (40)$$

where, λ_k are the constants for the mean-reversion velocities, $\sigma_{k,t}$ are the volatility functions and $L_{k,t}$ is a Poisson Lévy process with $L_{k,t} = \int_0^t \int_0^\infty z dN_{k,s,z}$, where, N_z is PRM.

Considering the above, the solution as in Eq. (30) then rewrites to:

$$\begin{matrix} X_{k,t} = x_k ex\,p(-\lambda_k t) + \\ + \int_0^t \int_0^\infty exp\,(-\lambda_k(t-s)\sigma_{k,s} z\, dN_{k,s,z} \end{matrix} \quad (41)$$

The resulting wind power production index is then simplified by setting $a_k = 1, \forall k$ and $\mu_t = 0$, yielding:

$$Y_t = \sum_{k=1}^{n} X_{k,t} \quad (42)$$

In the absence of an explicit seasonal effect, the wind power production index Y_t bound within the definition limits reads as:

$$U_t = min\,(Y_t, 1) \quad (43)$$

Applying this to the wind power future price yields (Hees, 2021):

$$F_{t,T} = 1 - \int_0^\infty \frac{1 - iu - exp(-iu)}{2\pi u^2} exp\,(A_t(u,T))du \quad (44)$$

with a defined function $A_t(u,T)$ as depicted in the publication. For the time dynamics df, Hees (2021) derives:

$$df_{t,T} = \sum_{k=1}^{n} \int_{D_k} \gamma_k(t,z,T) d\widetilde{N}_k^Q(t,z) \quad (45)$$

where, $\widetilde{N}_k^Q(t,z)$ are the Q compensated PRMs and gamma is a stochastic process defined as $\gamma_k(t,z,T) = \int_{0+}^{\infty} e^{A_t(u,T)} \frac{1-iu-e^{-iu}}{2\pi u^2}[1 - e^{iu\theta_k(t,z,T)}]du$ within the time interval $0 \le t \le T$.

[2] The vector b can be represented as $b = \begin{bmatrix} b_0 \\ b_1 \\ \dots \\ b_{p-2} \\ b_{p-1} \end{bmatrix}$.

3.4.3. Risk premium

Equation (27) holds true also for the Lévy process approach. In the special representation by Hees (2021), the risk premium $R_{t,T}$ is analytically derived as:

$$R_{t,T} = \int_{0+}^{\infty} \frac{1 - iu - e^{-iu}}{2\pi u^2} [e^{H_t(u,T)} - e^{A_t(u,T)}] du \quad (46)$$

3.4.4. Pricing of options

On top of the modelling of the derivatives, Benth and Benth (2009) and Benth and Pircalabu (2018) expand the models by including the pricing of options. The call option price is then derived as:

$$C_{t,K,\tau_1,\tau_2,\tau_K} = exp(-r(\tau_K - t))\, E(max(F_{t,\tau_1,\tau_2}) - K, 0 | \mathcal{F}_t) \quad (47)$$

where, K is the strike price, τ_1 and τ_2 defines the start and the end of the contractual period for the derivative, τ_K is the exercise time for the wind power future, and r is the risk-neutral interest rate. Obviously, the time elements shall obey $t < \tau_K < \tau_1 < \tau_2$.

4. EQUILIBRIUM PRICING MODEL

Equilibrium models capture the fundamental economics of rational risk-averse market participants and explain their trading behaviour based on a risk premium size, structure and driver. As such the underlying strategies for risk premia can be assessed. For this Gersema and Wozabal (2017) introduce a game with two different players, the owners of wind power plants and the owners of conventional generation plants. The goal of the model is to investigate the hedging strategy of both players to mitigate their respective risks.

4.1. Equilibrium price market model

Gersema and Wozabal (2017) propose a model with the assumption of a homogeneous group for both players, which is valid under pure hedging and neglecting individual factors. Furthermore, the expected utility by each player is linearly related to the expected profits and variance. The utility $U(\bar{\pi})$ of a player with respect to the average profit $\bar{\pi}$ is defined as:

$$E(U(\bar{\pi})) = E(\bar{\pi}) - \lambda/2\, Var(\bar{\pi}) \quad (48)$$

where, λ is the risk aversion with zero representing neutrality and positive values scaling the risk aversion. $Var(x)$ represents the function to obtain the variance of x and $E(x)$ yields the expectation value of x.

Therein the profit is composed of a component from the average general business profits $\bar{\rho}$ [3] and the profits from the wind power futures $Q(F_t - F_T)$, with the volume of the futures Q, the futures start price F_t and the future's price at maturity F_T, as:

$$\bar{\pi} = \bar{\rho} + Q(F_t - F_T) \quad (49)$$

By maximizing the overall utility of each player via a first-order condition, the optimal quantity of wind power futures is received as:

$$\hat{Q} = \frac{F_t - E(F_T)}{\lambda Var(F_T)} + \frac{Cov(\bar{\rho}, F_T)}{Var(F_T)} \quad (50)$$

The first term is a speculative position, which is valid for both players and dependent on the volume of futures with their price difference between start and maturity. Its profit relates directly to the change over time in the future. To maintain a stable futures market, the quantity of wind power futures for both wind power producers and conventional generators must be balanced. The hedging position, represented by the correlation between operational profits $\bar{\rho}$ and futures prices at maturity remain independent of risk aversion.

The resulting equilibrium price is then given as:

$$F_t = 100\, E(\bar{W}) - \xi((Cov(\bar{\rho}_W, \bar{W}) + (Cov(\bar{\rho}_C, \bar{W})) \quad (51)$$

with the indices W and C representing the wind power producers and the conventional generators respectively, the factor ξ represents the risk aversion ratio with:

$$\xi = 100 \frac{\lambda_W \lambda_C}{\lambda_W + \lambda_C} \quad (52)$$

and the average wind capacity factor $\bar{W}$ over the measurement period T is:

$$\bar{W} = \frac{1}{T} \sum_{h=1}^{T} \bar{W}_h \quad (53)$$

The first term in Eq. (51) is a risk-neutral expectation value, while the second term comprises the risk premium. The risk premium is thereby steered by the sign and amount of the covariance of the average wind capacity factor and the respective operational profits of each player.

To evaluate this covariance, the operating profits are derived for the wind power producer as:

$$\overline{\rho_W} = P \sum_{h=1}^{T} K_h \overline{W_h} \quad (54)$$

where, P is the constant power market price and K_h is the total wind generation capacity of the producer's assets. This assumption is justified based on the feed-in tariff-based and auction-based pricing.

For the conventional generator, the corresponding general business profits are:

$$\overline{\rho_C} = \sum_{h=1}^{T} P_{Ch} R_h - b \frac{R_h}{\mathrm{E}(R_h)^{\zeta - 1}} \quad (55)$$

[3] General business profits in this instance mean operational profits that are generated by the wind or conventional power generation. Any financial market instrument related profits as by the wind power futures are explicitly excluded.

where, P_{Ch} is the fluctuating power market price at the power exchange and R_h is the residual load. The second term is the cost function with an exogenous chosen scaling parameter b to match historical data, and the parameter ζ controlling the convexity of the cost function.

4.2. Economic model by simulation of variables

The outlined model is based on four random variables: the wind capacity factor $\overline{W}$, the solar generation G, system-wide demand D and spot power price P_{Ch}. It is hourly-based (Gersema & Wozabal, 2017). These variables are modelled using a stochastic model in two steps. Firstly, the seasonal trend component is captured through kernel regression, forecasting capacity factors for wind and solar power production, adjusted for capacity additions. Wind forecasts are daily-based, while solar forecasts consider 24 distinct values per day to address intra-day variance. Hourly realizations are then modelled through block-wise bootstrapping of hourly deviations from a deterministic trend, with random residuals selected in weekly blocks to preserve serial correlation across three seasons (summer, winter, transition). Day-ahead prices are modelled in a linear regression with the parameters of daily temperature, daily prices for natural gas, and minutes between sunrise and sunset (Gersema & Wozabal, 2017).

5. FINDINGS FROM EXISTING MODELS

The present models all relate their model results to real-world data and derive conclusions relevant to the market. This section summarizes these findings, noting any differences where applicable. Overall this gives an overview of the critical elements that need to be reflected in any model.

5.1. Wind utilization

The wind capacity factor exhibits a seasonal trend, with winter months having higher utilization compared to summer. In January, utilization averages 24.9%, while in July sees only 11.8%. April and October fall in between. Winter has the highest standard deviation, indicating higher absolute and relative risk compared to summer. Symmetrization of Gaussian risk factors shows a positive skewed function, with the median smaller than the mean (Gersema & Wozabal, 2017). The seasonality as such has to be reflected in any model.

5.2. Wind power future prices

Future prices closely match forecasted values from models by Benth and Pircalabu (2018), Melzer et al. (2017) and Gersema and Wozabal (2017) indicating the effectiveness of these models in describing wind power futures. Expected future prices show a linear increase for wind power producers and a linear decrease for conventional generators. With wind power producers bearing a risk premium, the intersection of price and demand for wind power futures is anticipated to shift towards higher prices and lower quantities. Notably, the overall traded volume remains constant across months, with variations primarily in prices affecting market volume (Gersema & Wozabal, 2017).

5.3. Risk premium

The publications by Benth and Pircalabu (2018) and Melzer et al. (2017) analyze wind power futures using a no-arbitrage pricing model, comparing actual prices with predicted ones to determine the risk premium. Disagreement arises on whether the risk premium is perceived as positive or negative. Melzer et al. (2017) find a decreasing negative risk premium for longer contractual times and maturity, while Benth and Pircalabu (2018) suggest an inter-annual and contract-specific dynamic. They also note an increasing risk premium for short-term deliveries due to low market liquidity and short-term weather forecasts, which are not modelled. The risk premium for weekly and monthly contracts tends towards zero towards the time of maturity when the weather forecast for the delivery period gets sufficiently accurate to neglect wind volume risks. The seasonality of the risk premium of weekly contracts is positive in winter and negative in summer. In contrast, in energy futures, the risk premium is increasing and even reaches a positive value for times close to delivery (Benth & Pircalabu, 2018). A similar trend can be expected and seen for wind power futures. This would yield an even higher risk premium in times of high volatility, meaning during winter times.

The risk premium is influenced by factors such as the convexity of the cost function for conventional generators and wind compensation and capacity increase for wind power producers (Gersema & Wozabal, 2017). In terms of the power demand, it is indirectly related to the hedging discount. This is based on the proportionality of the conventional generator's volume and profit on the power demand. Further a higher demand likely also yields higher market prices for power and thus higher profits for conventional generators.

Risk aversion parameters affect the absolute size of the risk premium but not its sign. Calculated risk levels are significantly higher than expected profits, indicating high risk aversion in the market (Gersema & Wozabal, 2017). The calculated risk levels for each euro of variance are weighted in the range of two to seven times as high as the expected profit (Gersema & Wozabal, 2017). This is in line with risk aversion on relative returns and yields a risk aversion in the range of $\lambda \sim 10^{-8}$. This is in line with the size of the risk aversion factor in other areas of research.

5.4. Challenges of wind power futures

The equilibrium model by Gersema and Wozabal (2017) demonstrates asymmetric risk volumes for wind power producers and conventional generators due to differences in operational profit correlations. This inequality in risk leads to varied demand for wind derivatives. Hedging efficiency, as highlighted by Gersema and Wozabal (2017), depends heavily on the correlation between a producer's utilization and the overall utilization, affecting the suitability of wind power futures as hedging tools. Custom-made OTC contracts may be preferable in cases of low correlation. The inefficiency of current wind derivatives markets, attributed to the lack of an accurate evaluation model, discourages investor participation compared to temperature derivatives markets, contributing to low market capitalization and limited interest from financial institutions in wind power derivatives.

The hedging efficiency is a major driver for the acceptance and spread of the respective wind power futures. It depends heavily on the correlation of the producer's utilization with the overall utilization, as the currently traded wind power futures by NASDAQ and EEX are based on an aggregated index. In the example of EEX in Germany, this would be the utilization in Germany and the utilization by the individual wind power producers in Germany. As derived for the Amprion zone the correlation between the overall EEX index and the Amprion utilization is at 0.79, for Tennet at 0.97, for 50Hertz at 1.00 and for Transnet at 0.58. This trend is confirmed by a comparison of the actual wind power production to a synthetic index representing the NASDAQ underlying index as done by Benth and Pircalabu (2018). In contrast, a wind power producer located in the Transnet zone would not see the EEX wind power futures as a suitable hedging tool, as it does not correlate well with the wind volume risks in its area and OTC is preferable. For a wind power producer in the 50Hertz zone, the EEX wind power futures would be an excellent option due to a perfect correlation.

In the case of the US Futures Exchange's wind power futures, this effect was especially dominant as the underlying index represented discrete areas in New York state and Texas. While this is of benefit for these respective represented discrete areas, the hedging efficiency can be believed to be low for any other wind power producers. This can also be seen as one of the reasons for its collapse (Alexandridis & Zapranis, 2013). As a way out of this dilemma, location-specific pricing could be applied, at the expense of a simple structure.

While there is demand for wind power and hedging tools to manage wind volume risk, investors appear hesitant to engage in wind derivatives, unlike the positive growth trend observed in temperature derivatives. One contributing factor to this reluctance among financial institutions could be the absence of a widely accepted model for accurately and reliably evaluating these derivatives, leading to low market capitalization and diminished interest in wind power derivatives (Alexandridis & Zapranis, 2013).

5.5. Changes in the power market not reflected in models

All models presented in prior literature are based on data prior to 2021. The electricity spot market in Europe has undergone several changes since then. On an observable note, the price spread is increasing. As an example, Germany experiences an increase in the number of hours with negative prices and more and more curtailment of renewable power assets. On the negative prices, 2021 showed 140 hours, 2022 — 69 hours, 2023 — 301 hours and the first half of 2024 (until July) had already 305 hours. Grid constraints and renewable production exceeding demand led to a record high of 10 TWh of curtailed renewable energy in 2023 in Germany (EEX, n.d.).

These changes were partially also induced by the rapid growth in solar power generation assets in the European and especially the German grid (Schöniger & Morawetz, 2022). German solar capacity increased from 60 GW to over 80 GW between 2021 to 2023 (Bundesnetzagentur, 2024). This is a rapid increase compared to the relatively shallow additions in the timeframe of the model's observations.

Taking these into consideration, an updated model would need to properly reflect the curtailment risk and the negative price risk. The negative hours and the as-produced solar generation show a high correlation (Biber et al., 2022; Prokhorov & Dreisbach, 2022). The model is proposed to formulate the indirect effects of solar generation and the induced risk of curtailment based on overproduction and negative prices. The production from solar would thus have a negative effect on the price potential for the wind assets.

6. CONCLUSION

The motivation for wind power futures originally stemmed from changes in the wind market regulations, especially in Germany. It was intended as a hedging tool for developers and generators to derisk the production risks of wind farms. Following this, also literature on wind power futures emerged with models describing the real production cases and presenting an analytical result of the risk premium. These models included no-arbitrage pricing models, using a seasonal element and a stochastic short-term term. Notably, the TFS approach and the Lévy process are popular due to their modelling efficiency and ability to handle skewed data. Another unrelated approach is the equilibrium price approach to derive optimal strategies for wind power producers and conventional generators.

Analysis of actual wind power data by the existing models in a pre-2021 setup on the NASDAQ futures reveals inconclusive findings on risk premiums, with some studies observing seasonal variations in the risk premium. For instance, a positive risk premium is noted in winter, and a negative one in summer, due to differing production risks and volatility hedging needs. These risk premiums also vary asymmetrically between wind power producers and conventional generators.

With changed market characteristics since 2021, which culminate in increased price spreads and more negatively priced hours, the modelling without such reflections limits the future risk reflection to real market data. The existing models are hence suggested to be expanded by incorporating such effects, which are indirectly linked to the weather uncertainties for solar power generation. We hope that upcoming research will ensure this expansion and derive direct applications under these new market conditions. On top of the above, no-arbitrage models currently do not account for information gained as the maturity of the future approaches, which affects risk premiums. Incorporating factors like accurate weather forecasts could address this. Applying the adapted models to EEX data, which hasn't been covered yet, could confirm the adapted model's accuracy, especially for the focus markets in Europe.

On the side of equilibrium price models, it was identified that the absence of investors in the models poses limitations. Investors as a potential player shall be included in subsequent models to fully cover their incentives and drives, which are yet unexplored. Unlike the no-aritrage models, the equilibrium price models are agnostic — in principle — to the market characteristics of added solar power and increase fluctuations., Hence, the recent market changes do not require adaptatons in the model, but require a recalculation of the model under revised input conditions.

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