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Stochastic modelling and forecasting of wind capacity utilization with applications to risk management: The Australian case

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ABSTRACT

Wind electricity generation in Australia is accelerating, and South Australia has one of the highest penetration rates globally, so pricing and hedging risks associated with wind power generation are becoming of critical importance. This paper proposes stochastic models for the dynamics and attributes of wind capacity utilization, a typical underlying asset of wind derivatives. Using daily wind generation data from the five states of the Australian national electricity market, we will identify the nature of wind capacity utilization (generation/capacity) in terms of seasonality, mean reversion, and roughness. We employ rough and Lévy stochastic models to capture these dynamics and gauge their efficiency for calibration applications. Finally, we will assess the forecasting performance of the proposed models. This research will offer practical insights into the role of wind derivatives in the energy transition and the integration of wind energy into the electricity markets.

1. Introduction

1.1. Brief background and context

Wind derivatives are financial instruments that offer financial security against risks associated with the variable nature of wind power generation, namely volumetric risk. Such derivatives are critical to managing the volumetric risk that can affect the revenues of energy producers, the investment management in renewable energy projects, and the sustainable growth of wind energy during the rapid transformation of the energy markets. The key building blocks for evaluating wind derivatives include the modelling of *wind capacity utilization (WCU)* and its forecasting. Note that WCU measures the amount of installed generated capacity that is effectively utilized. The aim of this research project is to develop a comprehensive framework for modelling and forecasting WCU.

The proposed modelling frameworks will offer useful tools for risk assessment practices and investment decision making for various stakeholders in energy markets. Firstly, accurate forecasting of wind capacity utilization will allow energy producers to optimize their operational efficiency, better manage financial risks and stabilize revenues through wind power derivatives, as well as negotiate favourable energy derivatives contracts. Furthermore, it will allow developers to identify the best sites for new projects

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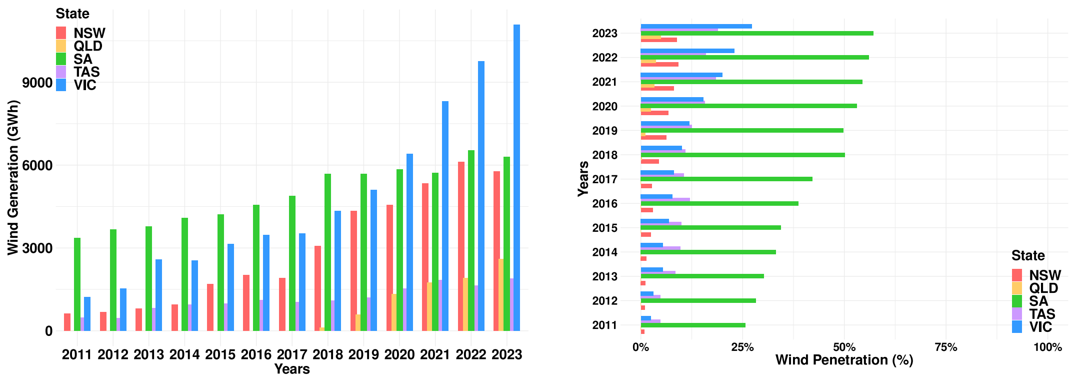

(a) Wind Generation (b) Wind Penetration

Fig. 1. Large-scale wind generation (left panel) and wind penetration (right panel) for NSW, SA, VIC, TAS, and QLD from 2011 to 2023.

and plan their investments more effectively. Project managers can use these forecasts to efficiently schedule maintenance, which in turn can reduce costs and avoid downtimes during high production periods. With a better understanding of wind capacity utilization, policymakers can develop effective incentives and regulations to support the reliability and expansion of wind energy. Regulators, such as the Australian Energy Market Operator (AEMO), can also benefit from using WCU forecasts to better understand the implications of wind energy variability on grid stability and market dynamics and in creating informed regulations and policies.

1.2. Australian wind generation overview

Australia pledged to achieve net-zero emissions by 2050 and committed under the Paris Agreement (2016) to reduce its carbon emissions by 26%–28% below 2005 levels by 2030. Thus, Australia is currently dramatically shifting its electricity generation mix from large, centralized coal-fired power generation and deploying variable renewable energy (VRE) more quickly than in any other period in its history. In 2019, the per capita installation rate of renewable electricity capacity exceeded that of the closest leading country, Germany, by a factor of 2.5. This rate was 4–5 times faster per capita than in the European Union, Japan, the USA or China and exceeded the global average by a multiple of ten (Stocks et al., 2019). The federal government also formulated several policies to increase the uptake of renewable energy, such as the 2001 Mandatory Renewable Energy Target (MRET), which was replaced by the 2009 Renewable Energy Target (RET). The RET sought to generate 23.5% of Australia's electricity generation capacity from large-scale renewable projects by 2020 (Forrest and MacGill, 2013). RET was met in 2019, a year earlier than planned, and installed capacity was sufficient to meet MRET (Stocks et al., 2019; CEC, 2024).[1]

The Australia's National Electricity Market (NEM) accounts for more than 90% of Australia's electricity demand and stands as one of the longest interconnected power systems globally. It spans five Australian states along the east and southeast coasts, stretching around 5000 kilometres and comprising roughly 40,000 kilometres of transmission lines and cables. These states include New South Wales (NSW), Queensland (QLD), Victoria (VIC), South Australia (SA), and Tasmania (TAS) (AEMO, 2021). Historically, wind farms have enjoyed a cost advantage over large-scale solar PV installations, as reflected in their lower Levelized Cost of Electricity. This economic efficiency led to a preference for wind energy projects to meet Large-scale RET in a cost-effective manner. Consequently, this resulted in the development of more wind energy projects in the NEM compared to utility-scale solar PV installations (Rai and Nunn, 2020). Wind generation has been a particularly significant form of VRE in SA, which recently set a global record by meeting more than 100% of its electricity demand from VRE for several hours (AEMO, 2020b; AER, 2021; Willis, 2023). SA also stands out globally, being second only to Denmark in terms of the annual share of VRE in its generation mix—a significant proportion of which comes from wind generation. Fig. 1 illustrates the growth of wind penetration (the ratio of wind generation to total consumption) in the NEM over time. SA leads with the highest wind penetration, exceeding 50%. Meanwhile, other states, such as VIC and NSW, are also witnessing significant growth in wind generation. In fact, VIC's increase in wind generation/capacity has now surpassed that of SA.

Our focus on wind generation within the NEM stems not only from wind's role as the primary VRE source and the varying penetration rates across different states but also from the complexities of forecasting wind generation. Unlike solar power,[2] where production is more consistent and is mainly influenced by time of day and weather, wind speeds can change rapidly and

[1] The RET establishes a goal to generate an additional 33,000 gigawatt-hours (GWh) of renewable electricity annually from the year 2020 through 2030. Australian states like Victoria and South Australia have also set ambitious renewable energy goals exceeding national objectives. Victoria has set renewable energy targets of 40% by 2025 and 50% by 2030. South Australia aims for 100% renewable energy by 2030 and plans to generate renewable energy that exceeds five times its current local electricity demand by 2050 (AER, 2021).

[2] Compared to wind energy, solar power is relatively newer in the NEM, with substantial generation beginning only in 2018. It also plays a smaller role in the energy mix than wind power.

unexpectedly, impacting energy output. Consequently, solar power exhibits lower day-to-day variability than wind, enabling mid-load power plants to effectively adapt their output to meet residual demand, helping to prevent significant and frequent price surges (Kyritsis et al., 2017; Mwampashi et al., 2022).

1.3. Considerations in wind power derivatives markets

Renewable energy producers face two main risks. One is the market price risk related to the price at which the generated power is sold. The second risk is the volumetric risk driven by the uncertainty of the produced power due to the intermittent nature of renewable energy sources subject to weather conditions. Wind power derivatives can be used to manage these risks. For example, producers use power purchase agreements (PPAs) to hedge their price risk, while, wind power futures can be used to hedge volumetric risks. In addition, stakeholders with indirect impact, such as conventional power producers and investors in wind energy projects, seek financial products to manage their exposure to the volumetric dependence of electricity price fluctuations. Pricing of wind power derivatives was originally performed based on wind speed models (Benth and Benth, 2009, 2010; Benth and Šaltytė, 2011), while most exchanges and over-the-counter markets used indices aggregating historical wind speeds over different periods. Using power conversion models, the wind speed could determine the power of the energy produced. However, indices compiled from meteorological data, such as wind, are prone to errors from power conversion models and aggregation procedures of wind data. Thus, recent theoretical and empirical research works employ models for the WCU, which is calculated based on actual generation data as wind power generation scaled by its capacity (Benth et al., 2021; Härdle et al., 2021). The WCU accounts for trends in wind power generation by considering variations in the utilization of installed capacity, and takes values between 0 and 1, capturing the efficiency of installed wind power generation. Furthermore, wind power generation is variable and weather dependent, imposing seasonal effects, and accurately modelling the high volatility of such dynamics becomes critical.

Management of such risks could be relevant at the state or country level, but most likely also at the level of individual wind farms. Therefore, the modelling frameworks should capture the dynamics of each farm, as well as the impact of the systemic risk of the corresponding power market (Benth et al., 2021).

Other considerations may be related to the liquidity restrictions of these markets and the fact that they are typically incomplete markets (Kanamura et al., 2021). Concerns about the establishment of arbitrage-free electricity markets in the "financial sense" can be addressed by using an equivalent pricing measure (Benth et al., 2018) or by recognizing that typically[3] standard "buy and hold" arguments do not hold in electricity markets due to its non-storable nature (Bennedsen, 2017).[4]

1.4. Research questions

In this paper, we will perform a comprehensive analysis of WCU factors in the Australian wind power market to offer practical insights to stakeholders and policy makers. This study will address three research questions:

1. What are the key empirical characteristics of WCU in the Australian wind power market?
2. What is a suitable stochastic modelling approach to capture the empirical dynamics of wind capacity utilization?
3. To what extent do these stochastic models of WCU enhance forecasting performance with material impact on risk management strategies for volumetric risk?

The outcome of this study will offer insight of practical relevance in the design of financial products related to wind power generation, the pricing of wind derivatives, and risk management in wind power generation.

Progressing to the Pacific-Basin Finance Journal (PBFJ) pre-registration publication process, our original approved research pitch (based on (Faff, 2015)) is presented in A, and is expanded in this pre-registered report for Phase 3 of the PBFJ pre-registration publication process in accordance with (Faff, 2023). Section 2 presents a review of the associated literature and the motivation for this research. Section 3 discusses the research idea and the value proposition to the associated stakeholders. The empirical design and the stochastic modelling used to address the research questions are presented in Section 4. The contributions and impact of this research are summarized in Section 5.

2. Literature review

2.1. Three key papers

This study is motivated and extends the work by Benth et al. (2021), Kanamura et al. (2021) and Bennedsen (2017). WCU (or wind indexes) in Germany is studied by Benth et al. (2021). By employing a univariate Ornstein–Uhlenbeck process driven by a non-decreasing Lévy process, Benth et al. (2021) model idiosyncratic and systemic risk of WCU and compute the market price of risk. Furthermore, Benth et al. (2021) consider hedging applications of volumetric wind risk using a minimum-variance hedge of tailor-made wind futures contracts. In an attempt to address the shortcoming of the illiquidity of wind derivatives markets, Kanamura

[3] Electricity cannot be readily stored, unless other mechanisms like batteries or pump storage are introduced in the system.

[4] Establishing arbitrage-free markets becomes critical when evaluating wind derivative contracts, which is beyond the purpose of this paper but the focus of one of our upcoming papers.

et al. (2021) propose good-deal bounds pricing models for wind power futures, where wind power utilization (or loads) features mean-reversion and continuous-time seasonality. The upper and lower bounds represent the buying and selling prices in incomplete markets. Kanamura et al. (2021) also conduct an empirical analysis and computed numerically the futures prices of wind power, the associated limits, and the model risk premium. Although both of these two modelling approaches take into account stylized features of wind capacity utilization, such as seasonality and mean-reversion, they model uncertainty with standard Brownian motion.

There is strong empirical evidence that financial markets and commodity markets exhibit roughness in their dynamics. While there are many papers modelling electricity prices with stochastic dynamics driven by standard Brownian motion, there are very few considering rough dynamics. A notable exemption, Bennedsen (2017) proposes a rough model (via a modulated Brownian semistationary process) for electricity markets and provides statistical evidence of roughness in several European electricity markets that is associated with improved short-term forecasts of electricity prices. Note that electricity prices and WCU share similar characteristics, including seasonality, mean-reversion, and stochastic volatility. Motivated by Bennedsen (2017), we propose a rough model for WCU to evaluate forecasting performance.

Furthermore, these studies focus on European markets, e.g. the German wind power markets. There are no empirical studies investigating the dynamics of WCU in Australia, which represents an energy-only market with one of the highest wind penetrations worldwide.

2.2. Broader literature

Wind derivatives have been modelled using equilibrium pricing models (Gersema and Wozabal, 2017), and risk-neutral pricing. The risk-neutral approach is the most developed and includes early studies of modelling wind derivatives based on speed indices (Benth and Benth, 2009, 2010; Härdle and López Cabrara, 2012). However, recent studies consider risk-neutral pricing of wind derivatives on wind power utilization that is modelled by Ornstein–Uhlenbeck or Lévy processes, including works by Benth et al. (2018), Benth and Pircalabu (2018) and Benth et al. (2021). For example, Benth et al. (2021), beyond modelling wind utilization in wind farm level and in aggregate index level, they propose optimal hedging strategies using wind power futures to manage volumetric wind risk.

Advances in this line of research are as follows. The underlying wind power production index is modelled by Hess (2021) using an arithmetic multi-factor pure-jump Ornstein–Uhlenbeck model with time-dependent coefficients, to obtain tractable corresponding futures prices and associated risk premium. Kanamura et al. (2021) also model the wind power production index, although using good-deal bounds models to address the illiquidity concerns and derive the model risk premium. Furthermore, Härdle et al. (2021) use Gaussian and non-Gaussian continuous-time autoregressive moving average CARMA(p, q) models for weather derivatives embedding very skewed underlying assets and seasonal volatility (via extreme event modelling). However, despite the proximity of the wind power utilization dynamics to rough features, modelling wind utilization via rough dynamics remains an unexplored research field.

Modelling the dynamics of financial time-series with fractional Brownian motion originated by Mandelbrot and Van Ness (1968) and was revived by Gatheral et al. (2018) who demonstrate that log-volatility behaves as a fractional Brownian motion with Hurst parameter around an order 0.1 at any reasonable time scale. El Euch and Rosenbaum (2018) proposes a rough version of the (Heston, 1993) model as a limit of simple pure jump models of order flow. Rough models for forward price dynamics have also been developed by El Euch and Rosenbaum (2018), Abi Jaber et al. (2019) and Gatheral and Keller-Ressel (2020) that offer tractability at different levels. Empirical studies employing rough dynamics in the electricity markets (Bennedsen, 2017) and in the commodity markets (Alfeus and Nikitopoulos, 2022; Alfeus et al., 2024) confirm the importance of such dynamics in better capturing stylized features of commodity markets and offering improvement in forecasting performance. This paper will extend these contributions to modelling and forecasting the underlying building block of wind derivatives, namely, the wind power utilization. This extension can be also applied to other energy derivatives such as solar derivatives.

2.3. Motivation

Why study Australian wind capacity utilization? The high penetration of VRE in Australia (and worldwide) has introduced challenges that have not previously been encountered. States such as SA are known for having one of the world's most unpredictable and variable generation mixes of wind and solar PV (Power Runner, 2022), while other Australian states are growing fast their VRE penetration. Consequently, Australia's NEM serves as an excellent laboratory for studying the impacts of high and gradual integration of renewable energy in the market, as well as for exploring how these renewables can be modelled, priced, and managed in terms of the risk associated with intermittent energy sources. Our focus on Australian WCU aims to provide a foundational building block for pricing and managing risks associated with wind derivatives, an area where studies are notably lacking, especially compared to related studies based on European and US power markets. Most importantly, there is an urgency to understand the rapidly growing and transforming power markets and to design and price financial products, which are critical to supporting the energy transition in Australia, but also with benefits on a global scale.

Why re-evaluate existing models?

Studies on modelling and pricing wind power derivatives use different stochastic modelling approaches, and a comprehensive study is needed to identify the necessary features of these models that are supported by empirical observations. For example, what are the critical empirically observed features of WCU that models must include? How to best capture the seasonality, the mean-reversion and the volatility of these data series? Would Lévy models and/or rough models suffice to capture the dynamics of wind capacity utilization? These models have been applied to financial and commodity markets, and this study explores the ability of these models to (a) capture empirical features of WCU and (b) offer effective forecasts. Moreover, research on modelling energy derivatives (such as wind power futures and PPAs) is now in demand due to fast-growing and urging transition in the power generation sector. Modelling capacity utilization factors offers the first step towards addressing these challenges.

Why forecast wind capacity utilization?

WCU and their forecasts are the building blocks for evaluating financial products in wind power markets and assessing associated risks. For example, accurate forecasts of the expected intermittent wind power output are essential to determine the pricing structure of PPAs and enable more effective hedging against financial risks of fluctuating wind outputs and energy prices. These forecasts can also be useful in pricing and risk management of other similar contracts, including Contracts for Difference (CFDs), Feed-in Tariffs (FiTs), and Feed-in Premiums (FiPs) (OIES, 2024). Accurate forecasts can reduce the financial variability that parties under CfDs need to hedge against, thus providing a more stable investment and potentially lowering the cost of capital for renewable projects. For FiTs, regulators can adjust rates to ensure that they align with actual production levels and avoid scenarios of overcompensation (or undercompensation). Similarly, for FiPs, accurate forecasting can help set appropriate premiums over the market price. Furthermore, accurate power utilization forecasts allow investors to assess the profitability of wind farm projects, as well as banks and financial institutions to determine the necessary financing for wind farm projects. Reliable power utilization forecasts are also critical for market participants and traders for effective decision-making related to optimal volumes of electricity delivery in advance (day-ahead and month-ahead markets).

3. Theory (idea)

3.1. Idea

The NEM is unique as it is an energy-only market that connects states with diverse generation portfolios and leading VRE penetration rates. Moreover, while many countries are witnessing an increase in VRE penetration, SA stands out. In 2019, only two interconnected power systems operated for periods where wind and solar energy exceeded demand: Denmark (157%) and SA (142%) (AEMO, 2020a). However, SA's situation is also distinct, unlike Denmark, which is well integrated into European and Scandinavian power networks with connections to multiple countries, such as Germany, Norway, Sweden, and the Netherlands. Denmark can import up to 2.5 times its average demand through these links (Power Runner, 2022). In contrast, SA is linked only to VIC through two interconnectors, with an import capacity of 820 MW, roughly half of SA's average demand Mwampashi et al. (2021). Therefore, Australia serves as a unique case study for analysing attributes and forecasting the dynamics of WCU.

This research project will develop a comprehensive framework for modelling and forecasting WCU. This framework will contribute to providing tractable and robust models for wind derivatives such as wind power futures and PPAs. Such derivatives are vital to manage volumetric risk, optimize investments, and support sustainable growth of wind energy in the context of a dynamic and evolving energy landscape. The idea is to combine Australian wind generation data per state as well as at the wind farm level to first understand the dynamics of wind power utilization and their statistical and stochastic features. Then, informed by the features of the WCU dynamics, we will propose appropriate advanced mathematical models that would capture these dynamics and provide improved forecasting performance while minimizing computational effort. WCU is the building block for pricing wind derivatives, thus a comprehensive study of the dynamics and the development of stochastic models for WCU will contribute in constructing tractable models for wind derivatives with practical relevance. These models would be useful for risk assessment practices and investment decision-making for wind power producers, conventional power producers, wind power developers and managers, and energy market regulators and policy makers.

4. Empirical design (data and tools)

4.1. Data

For this analysis, we focus on five states in the NEM: NSW, VIC, QLD, SA, and TAS. We use daily data aggregated from high-frequency 5 min intervals, obtained from NEOpoint (2024), covering the period from 2011 to 2023. The dataset includes large-scale wind generation and installed wind capacity for each state. The installed capacity per state represents the total registered capacity—the maximum amount of electricity a facility can produce at any given moment across all wind farms in that respective state. We estimate the daily wind capacity utilization—how much of the installed generated capacity is effectively utilized in terms of power output relative to its maximum potential capacity for each state on a given day by

$$U_{s,d} = P_{\text{avg},s,d}/C_{\text{max},s,d}, \tag{1}$$

where $P_{\text{avg},s,d}$ is the average power output in megawatts (MW) for state s on day d, $C_{\text{max},s,d}$ is the installed capacity in MW for state s on day d. We aggregate five-minute wind generation data measured in MW to daily intervals by calculating the mean. The average daily wind generation is thus estimated by taking the sum of all 288 five-minute intervals within a day and dividing by 288 to obtain the mean value, that is, $1/288\sum_{i=1}^{288}\text{Generation}_i$, where Generation_i is the power output in MW for the ith five-minute interval of the day.

We also study the dynamics of WCU for nine SA wind farms, see Table 1. These farms have distinct characteristics regarding their contributions in terms of capacity, geographic location, and technology/operational age.

Table 1
Wind farms in SA.

Wind Farm	Capacity (MW)	Operational	SA Location	Owner
Waterloo	260	2010	Mid-eastern	Palisade and Northleaf
Lincoln Gap	212	2021	Northern	Nexif
Hornsdale	102	2016 First stage	Northern	Neoen
Wattle Point	91	2005	Mid-southern	AFL
Lake Bonney Stage 1	81	2005	Southern	Infigen
Starfish Hill	35	2003	Mid-southern	Ratch Australia
Cathedral Rocks	66	2007	Western	Acciona and EnergyAustralia
Canunda	46	2005	Southern	Engie and Mitsui
Willogoleche	119	2019	Mid-eastern	Engie

4.2. Econometric methods

We first investigate the statistical properties of WCU factors, including seasonal effects, trends, presence of rough dynamics, and characteristics of correlation structures.

4.2.1. Seasonality and trend

Following compelling empirical evidence, we investigate seasonal patterns in the series of WCU factors. Driven by weather effects over different seasons of the year, seasonality effects are expected in weekly, monthly, bi-annual and annual frequency.[5] Truncated Fourier series of trigonometric functions have typically been used to capture such effects (Benth and Benth, 2009; Sætherø, 2018).[6] Thus, typically a continuous seasonal component is modelled with truncated Fourier series of trigonometric functional form with an intercept and a trend to accommodate trends, and weekly, monthly, and yearly seasonal patterns, such as

$$\begin{aligned} S_t = c_1 + c_2 t + a_1 sin\left(\frac{2\pi t}{7}\right) + a_2 cos\left(\frac{2\pi t}{7}\right) + a_3 sin\left(\frac{2\pi t}{90}\right) + a_4 cos\left(\frac{2\pi t}{90}\right) \\ + a_5 sin\left(\frac{2\pi t}{365}\right) + a_6 cos\left(\frac{2\pi t}{365}\right). \end{aligned} \tag{2}$$

Even though these continuous-time seasonal functional forms are better than dummies and more tractable, their shortcoming is that if we use too many factors, we may have overfitting issues. Furthermore, the patterns produced are too regular. More realistic seasonal patterns can be incorporated by adding seasonality to the model or using splines (Sætherø, 2018). To manage these issues, we use the Matlab *stepwiselm* function to test the statistical significance of these patterns and select the one that best fits the data series. The function builds linear models by iteratively choosing predictor variables based on statistical criteria, such as the p-value from the F-statistics. The initial model may include only an intercept or a predefined set of predictors. In the forward selection step, the model progressively adds variables that statistically improve the model, provided the improvements are significant. On the other hand, the backward elimination step removes variables that do not contribute to model efficacy. This process of alternating between inclusion and exclusion of variables continues until the model reaches a point where no addition or subtraction of any variable significantly improves the model's accuracy (MathWorks, 2024). This method helps prevent overfitting while still capturing the necessary predictive elements in the data. Each state and/or farm has idiosyncratic features in relation to wind capacity utilization, so different seasonal patterns may exist in these series. Thus, our method remains tractable and sufficiently accurate.

4.2.2. Roughness

Using a range of roughness estimators, we will empirically examine the presence of roughness in the WCU time series. In line with Bennedsen (2017), we propose the following roughness index estimators; the change-of-frequency (COF) estimator of (Lang and Roueff, 2001; Barndorff-Nielsen et al., 2013) , GEN, variogram, madogram, ABS, DFA, and AGG. We also test for the presence of rough dynamics using the Gatheral et al. (2018) approach to estimate both the Hurst parameter for the proposed stochastic rough model.

4.2.3. Mean reversion & correlation structures

Empirical evidence supports the importance of incorporating mean reversion and accounting for the correlation structure (Kanamura et al., 2021). Thus, in our modelling framework will allow for mean-reversion and take into consideration the correlation structure as explained in the next section.

This econometric analysis supports the importance of accounting for seasonal effects and potential trends and skewness. Thus, we seek a stochastic model for the deseasonalised-de-trended utilization. Further for modelling convenience, a logit transformation of this data series is customary to transform the data approximately to a normal distribution, as these data are typically skewed.[7]

[5] Intra-day patterns are also important but they are beyond the purpose of this paper.

[6] A comprehensive account of different approaches have been discussed in Sætherø (2018), including truncated Fourier series of trigonometric functions, splines, dummies or combinations of these methods.

[7] The logit transformation converts the original proportion, limited to values between [0, 1], into a new value ranging from [$-\infty$, $+\infty$]. This allows for the application of various statistical methods that require unbounded data.

To address spikes in transformed data, we set the cutoff three times the standard deviation from the mean, in line with methods in existing research (Ketterer, 2014; Bublitz et al., 2017). We replace the spiked values with the median of the respective series—a more robust approach to outliers. Such spikes can compromise the stability required for statistical methods and could skew the results and lead to incorrect interpretations. Empirical evidence of rough dynamics informs the choice of the model for wind capacity utilization. We develop rough stochastic models and compare performance with Lévy stochastic models which have been typically employed in the literature.

4.3. Stochastic modelling of wind capacity utilization

In this section, we present the stochastic modelling of WCU factors and introduce the mathematical frameworks that capture their dynamics. We begin with the WCU $U_{s,d} \in [0,1]$ from Eq. (1) (in Section 4.1) indicating the daily WCU on day d in the state s (or farm s). We transform this data series by taking the logit function, as follows:

$$Y_t = \log\left(\frac{U_{s,t}}{1-U_{s,t}}\right),\ t = 1, 2, \dots, \tag{3}$$

where $Y_t \in (-\infty, +\infty)$ represents the logit transformation of the WCU data. Next, we adjust for empirically observed seasonal effects by fitting a seasonal component S_t (see Eq. (2)) to isolate the stochastic component X_t driving the WCU. Thus:

$$X_t = Y_t - S_t, \tag{4}$$

where S_t represents the seasonal component identified by the data and X_t is the stochastic component of WCU. We propose two models for X_t: (a) a novel model driven by the fractional Ornstein–Uhlenbeck process, and (b) a classical model for WCU using the Lévy-driven Ornstein–Uhlenbeck process.

4.3.1. Fractional Ornstein–Uhlenbeck (f-OU) model

We assume that the stochastic component of WCU X_t follows mean reverting dynamics driven by a f-OU process, defined by the stochastic differential equation (SDE):

$$dX_t = -\lambda X_t dt + \sigma dB_t^H, \tag{5}$$

where $\lambda > 0$ is the rate of mean-reversion, X_0 is the initial value of X_t and $B^H = \left(B_t^H\right)_{t\geq 0}$ is a fractional Brownian motion[8] with Hurst index, $H \in (0,1)$. The unique path-wise solution to this SDE is given by:

$$X_t = e^{-\lambda t}X_0 + \sigma\int_0^t e^{-\lambda(t-s)}dB_s^H, \quad t \geq 0. \tag{7}$$

Here, the integral $\int_0^t e^{-\lambda(t-s)}dB_s^H$ exists as a path-wise Riemann–Stieltjes integral by utilizing partial integration.

The f-OU model involves three parameters; the Hurst parameter H, the volatility parameter σ, and the rate of mean reversion λ. The estimation of these three f-OU model parameters is conducted in three stages:

(a) **Estimation of Hurst Parameter** H: We estimate H using the COF estimator (Lang and Roueff, 2001; Barndorff-Nielsen et al., 2013) based on second-order differences:

$$\hat{H} = \frac{1}{2}\log_2\left(\frac{\sum_{i=1}^{n-4}(X_{(i+4)\Delta} - 2X_{(i+2)\Delta} + X_{i\Delta})^2}{\sum_{i=1}^{n-2}(X_{(i+2)\Delta} - 2X_{(i+1)\Delta} + X_{i\Delta})^2}\right), \tag{8}$$

where $\log_2(\cdot)$ is the base-2 logarithm, Δ denotes the sampling interval, and the terms in the summations represent second-order differences at different frequencies, i.e., $[X_{(i+4)\Delta} - 2X_{(i+2)\Delta} + X_{i\Delta}]_{i=1}^{n-4}$ and $[X_{(i+2)\Delta} - 2X_{(i+1)\Delta} + X_{i\Delta}]_{i=1}^{n-2}$ are the second-order differences of X at two different frequencies.

(b) **Estimation of Volatility** σ: We estimate σ by using the method-of-moments estimator by Wang et al. (2023):

$$\hat{\sigma} = \sqrt{\frac{\sum_{i=1}^{n-2}(X_{(i+2)\Delta} - 2X_{(i+1)\Delta} + X_{i\Delta})^2}{n(4-2^{2\hat{H}})\Delta^{2\hat{H}}}}, \tag{9}$$

where Δ again denotes the sampling interval.

[8] A fractional Brownian motion $(B_t^H)_{t\in\mathbb{R}}$ is a centred self-similar Gaussian process with stationary increments. B_t^H commonly represented as an integral with respect to (standard) Brownian motion W_t as

$$B_t^H = \frac{1}{\Gamma(H+1/2)}\left\{\int_{-\infty}^0 \left((t-s)^{H-1/2} - (-s)^{H-1/2}\right) dW_s + \int_0^t (t-s)^{H-1/2} dW_s\right\}. \tag{6}$$

(c) **Estimation of Rate of Mean Reversion** λ: For the estimation of λ, we based the estimation on the autocorrelation function of the process, in line with Bennedsen (2017):

$$\hat{\lambda} = \text{argmin}_{\lambda} \sum_{l=1}^{d} \left(\hat{\rho}(l) - \rho_{\text{f-OU}}(l; \hat{H}, \hat{\sigma}, \lambda)\right)^2. \tag{10}$$

Based on Bolko (2020), $\rho_{\text{f-OU}}(l; \hat{H}, \hat{\sigma}, \lambda)$ is given by :

$$\rho_{\text{f-OU}}(l; H, \sigma, \lambda) = \frac{\sigma^2}{2\lambda^{2H}} \Gamma(1+2H)\cosh(\lambda l) - \frac{\sigma^2 l^{2H}}{2} {}_1F_2\left(1; H + \frac{1}{2}; H+1; \frac{\lambda^2 l^2}{4}\right), \tag{11}$$

where ${}_1F_2$ is the generalized hypergeometric function and l is the lag length. Note also that the empirical sample autocorrelation is computed as follows:

$$\hat{\rho}(l) = \frac{\frac{1}{n}\sum_{i=1}^{n-l}\left(X_{i+l} - \frac{1}{n}\sum_{i=1}^{n} X_i\right)\left(Y_i - \frac{1}{n}\sum_{i=1}^{n} X_i\right)}{\sum_{i=1}^{n}\left(Y_i - \frac{1}{n}\sum_{i=1}^{n} X_i\right)^2}, \quad l \in \{0, \dots, d\}, \tag{12}$$

where d is the maximum number of lags.

4.3.2. Lévy-driven Ornstein–Uhlenbeck (Levy-OU) model

As an alternative to the f-OU process, we consider that the mean reverting dynamics (5) of X_t follow an Ornstein–Uhlenbeck process driven by a generalized Lévy process:

$$dX_t = -\lambda X_t dt + dL_t, \tag{13}$$

where L is a time-homogeneous Lévy process (see Spiliopoulos (2009)). This model has a unique strong solution:

$$X_t = e^{-\lambda t} X_0 + \int_0^t e^{-\lambda(t-s)} dL_s, \quad t \geq 0, \tag{14}$$

where X_0 is assumed to be independent of $\{L_t\}_{t\geq 0}$. Also we assume that $\mathbb{E}[L_1] = \mu$ and $\text{Var}[L_1^2] = \eta^2$.

The Lévy-OU model involves only three parameters; the mean parameter μ, the volatility parameter η, and the rate of mean reversion λ. Thus, we estimate μ, η and λ as follows:

$$\hat{\mu} = \frac{1}{n}\sum_{i=1}^{n} X_i,$$

$$\hat{\eta} = \sqrt{\frac{2}{n}\sum_{i=1}^{n}\left(X_i - \hat{\mu}\right)^2}, \tag{15}$$

$$\hat{\lambda} = \text{argmin}_{\lambda} \sum_{h=1}^{d} \left(\hat{\rho}(l) - \rho_{\text{Levy-OU}}(l; \lambda)\right)^2, \tag{16}$$

where $\hat{\rho}(l)$ is defined as in (12) and the autocorrelation function for the Levy-OU process is

$$\rho_{\text{Levy-OU}}(l; \lambda) = e^{-\lambda l}. \tag{17}$$

4.4. Forecasting

An important application regarding WCU is its forecasting that is integrated in the pricing of wind derivatives. For the empirical investigations, we consider forecasting horizons of 1 to 10 days. The forecasting exercise is used as a technique to calibrate the models and assess their performance. Such investigations could be useful for many applications including stochastic modelling of PPAs according to Biegler-König et al. (2022). Next, we explain how the forecasting performance will be evaluated and compared.

4.4.1. Forecasting with f-OU process

In line with Grimmett and Stirzaker (2001) (Section 9.2), and Bennedsen (2017), we forecast based on an f-OU process by using the best linear predictor. This predictor is based on the autocorrelation function of the rough (f-OU) process. For a given forecast horizon $h > 0$, our objective is to calculate the conditional expectation

$$\hat{X}_{t+h} = \mathbb{E}[X_{t+h}|\mathcal{F}_t], \tag{18}$$

where $\mathcal{F}_t = \sigma\{X_s, s \in [0,t]\}$ represents the information filtration generated by the process X. We employ the linear predictor of X_{t+h} given $X_1, X_2, \dots, X_t$ as:

$$\hat{X}_{t+h} = \sum_{i=1}^{t} a_i X_i, \quad h \geq 1, \tag{19}$$

where $a_a, a_2, \ldots, a_t \in \mathbb{R}$ satisfy the system of equations:

$$\sum_{i=1}^{t} a_i \rho_{\text{f}-\text{OU}}(|i-j|; \hat{H}, \hat{\sigma}, \lambda) = \rho_{\text{f}-\text{OU}}(h+j; \hat{H}, \hat{\sigma}, \lambda), \quad 1 \le j \le t, \tag{20}$$

with $\rho_{\text{f-OU}}$ denotes the autocorrelation function, see also Eq. (11).

4.4.2. Forecasting with Lévy-OU process

For the forecasting application, we consider two types of forecasting approaches using Lévy-OU processes. One approach using the best linear predictor, see Eq. (19), with the autocorrelation function in (20) being replaced by the corresponding autocorrelation function for Lévy-OU process, see Eq. (17).

The second approach considers the Gamma–Ornstein–Uhlenbeck (Gamma-OU) process. Specifically, we assume that the driving Lévy process L is a compound Poisson process. Accordingly, let $L_t = \sum_{k=1}^{N_t} Y_k$, where N_t is a Poisson process with intensity parameter a, and Y_k are independent identically distributed Gamma$(1, b)$ random variables. Consequently, we obtain that $X_0 \sim$ Gamma(a, b). The prediction equation for X_{t+h} for the Gamma-OU process is derived as follows:

$$X_{t+h} = e^{-\lambda h}\left(X_t + \int_0^h e^{\lambda s}\, dL_s\right) = e^{-\lambda h}\left(X_t + \sum_{i=1}^{\infty} \Gamma_L^{-1}\left(\frac{\alpha_i}{h}\right) e^{\lambda h r_i}\right), \tag{21}$$

where $\{\alpha_i\}$ and $\{r_i\}$ are two independent sequences of random variables (Spiliopoulos, 2009). The r_i are independent copies of a uniform random variable in $[0, 1]$, and $\{\alpha_i\}$ is a strictly increasing sequence of arrival times of a Poisson process with intensity 1. The function $\Gamma_L^{-1}(x)$ is defined as

$$\Gamma_L^{-1}(x) = \max\left\{0, -\frac{1}{b}\log\left(\frac{x}{a}\right)\right\},$$

where the parameters a and b are given by

$$a = \frac{2}{n}\frac{\left(\sum_{i=1}^{n} X_i\right)^2}{\sum_{i=1}^{n}\left(Y_i - \frac{1}{n}\sum_{i=1}^{n} X_i\right)^2}, \tag{22}$$

$$b = \frac{\sum_{i=1}^{n} X_i}{\sum_{i=1}^{n}\left(Y_i - \frac{1}{n}\sum_{i=1}^{n} X_i\right)^2}. \tag{23}$$

To evaluate the forecasting performance, we use the following three loss functions: Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and Akaike Information Criterion (AIC):

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(\widehat{X_{k+h}} - X_{k+h}\right)^2},$$

$$MSE = \frac{1}{N}\sum_{k=1}^{N}\left(\widehat{X_{k+h}} - X_{k+h}\right)^2,$$

$$\text{AIC} = N\ln(\text{MSE}) + 2p,$$

respectively, where N is the number of observations, and p is the number of free parameters.

5. Conclusion

5.1. What's new

This study provides novel theoretical and empirical contributions to research dedicated to modelling wind derivatives and evaluating their impact on pricing and risk management. More specifically, this study will expand existing research in the following new directions. Firstly, this will be the first study to analyse the empirical features of WCU in Australia. Secondly, we perform a comprehensive analysis of WCU characteristics with the aim of investigating new features beyond those previously used in the literature, including seasonality and mean reversion. We will investigate the roughness of the WCU time series and propose a more robust seasonality treatment. Third, we will propose a new class of models for WCU that accommodate the features observed empirically, namely the fractional Ornstein–Uhlenbeck (f-OU) processes, and compared them with the commonly used Lévy-driven Ornstein–Uhlenbeck (Levy-OU) processes. Lastly, we will conduct a forecasting analysis of the models to compare their performance for a range of forecasting windows.

5.2. So what?

The NEM provides a particularly interesting empirical laboratory for studying and modelling wind capacity utilization. Beyond being one of the longest interconnected electricity markets and leading global VRE integration, NEM is an energy-only market that includes five states with different VRE penetration levels and generation mix. Thus, the findings of this study will be valuable to national and international stakeholders in wind energy markets — from VRE producers to policy makers. Furthermore, modelling WCU is fundamental to pricing wind derivatives. Therefore, studying the dynamics and developing tractable and robust models have practical relevance for effective risk management practice and investment decision making in wind energy markets. In addition, from a theoretical innovation perspective, the modelling approaches proposed in this study can be used to model power utilization of other form of energy, especially intermittent energy sources such as solar. Generally, this research will offer useful risk management tools to help the energy transition in Australia and globally.

5.3. Contributions

Our research makes both theoretical and empirical contributions. In the theoretical domain and in relation to mathematical finance and energy finance, we propose advanced stochastic models (Lévy and rough models) that reflect the empirical characteristics of the wind power utilization and can also easily be extended to other VRE markets. These types of models have been used to effectively model financial and commodity markets, and this is the first time these models have been used and compared in the academic literature to model and forecast wind capacity utilization. We will investigate the ability of such models to capture key empirical features of these time series and to improve forecasting. The proposed class of models can capture dynamics of high frequency datasets (Bayer et al., 2016; Gatheral et al., 2018), thus these models can be extended to model intra-day variation of WCU factors (Garcin, 2022). These investigations will inform robust pricing methods for wind derivatives and risk management practice. In the empirical domain, we contribute to research that gauges the impact of the integration of renewable energy in electricity markets. Based on the versatile and unique Australian wind power market, we explore the statistical properties and characteristics of WCU in (the five states of) Australia. We also estimate the models by fitting to wind generation and capacity market data and then perform a forecasting performance analysis. These theoretical and empirical contributions will provide a more accurate forecasting of WCU with practical relevance. They can help wind power producers optimize operational efficiency that would help design favourable PPAs and stabilize their revenues. Wind power developers can also benefit from accurate WCU forecasting in planning and managing their investments. Energy market regulators and policymakers can also gain from better understanding WCU to inform market design and effective incentives and support schemes.

5.4. Other considerations

The research team includes two experts in the integration of renewable energy in electricity markets and three senior experts in stochastic modelling of financial and energy markets. Furthermore, one of the team members is affiliated with the following centres of the University of Technology Sydney: Centre of Climate Risk and Resilience, Centre for Business and Sustainable Development, Centre for Livelihoods and Wellbeing, and internationally, with the Commodity and Energy Markets Association, and the International Association of Energy Economics. Another team member is a principal investigator at the National Institute for Theoretical and Computational Sciences– Quantitative Finance Research Programme in South Africa. Thus, the outcomes of this project will be distributed to these networks, and will be presented to industry events to escalate the environmental and social impact of this research.

CRediT authorship contribution statement

Mesias Alfeus: Writing – review & editing, Writing – original draft, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Resources. **Muthe M. Mwampashi:** Writing – original draft, Methodology, Investigation, Conceptualization, Data curation, Formal analysis, Resources, Software, Validation, Visualization, Writing – review & editing. **Christina S. Nikitopoulos:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Conceptualization, Formal analysis, Resources, Visualization. **Ludger Overbeck:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization, Formal analysis, Resources.

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Appendix. Phase 2 pitching process

A.1. Phase 2 approved pitch

See Table A.1.

Table A.1
Phase 2 approved pitch.

Research team	Dr. Mesias Alfeus; Dr. Muthe Mwampashi; Assoc. Prof. Christina Nikitopoulos; Professor Ludger Overbeck
FOUR	Four aspects of BIG picture framing
A. Working Title	Wind Energy Derivatives: Modelling for Risk Management and Investment
B. Basic Research Question	How can stochastic modelling of wind energy derivatives enhance risk management strategies and inform optimal investment decisions in the renewable energy sector?
C. Key Paper(s)	Benth, F. E. and Benth, J. S. (2009). Dynamic pricing of wind futures. Energy Economics, 3: 16:24. Kanamura, T., Homann, L. and Prokopczuk, M. (2021). Pricing analysis of wind power derivatives for renewable energy risk management. Applied Energy, 304:117827. Gracianti, G., Zhou, R., Li S.H. and Wu, X. (2023). An assessment of model risk in pricing wind derivatives. Annals of Actuarial Science, 17: 479-502.
D. Motivation/Puzzle	Renewable energy is key to a safer, cleaner, and sustainable world and for reaching the target of net-zero emissions by 2050. Therefore, there is a shift in the global energy sector from fossil-fuel energy sources to renewable energy sources like wind, solar and batteries. This energy transition is driven by the increasing penetration of renewable energy into the energy generation mix, advances in energy storage and the emergence of electrification. Regulation and commitment to decarbonization have been mixed within countries, but the energy transition will continue to increase in importance as companies, economies and regulators prioritize environmental, social and governance (ESG) factors. Thus, industry, policy and researchers are working to address technical and socio-economic challenges in support of a decarbonized electricity future. Wind generation is a clean and cost-effective energy source, indeed is the cheapest source of large-scale renewable energy, with wind projects adding growth to national economies and leading to energy independence, as countries would not rely on imported fuel sources. However, the variable nature of wind generation dictates suitable models to price these energy commodities products. These models depend on factors such as wind speed, weather conditions, and rely on grid interconnection capabilities, and technological improvements in manufacturing and wind plan physics.
THREE	Three core aspects of any empirical research project i.e. the "IDioTs" guide
E. Idea	This research project aims to provide a comprehensive framework for modelling and managing uncertainty, optimizing investments, and supporting the sustainable growth of wind energy in the context of a dynamic and evolving energy landscape. The idea is to combine data from several sources to firstly understand the determinants of these energy derivatives and their features, and then propose appropriate advanced mathematical models that would provide improved pricing performance and minimize computational effort. Once an appropriate modelling framework has been established, then these models can be used for risk assessment practices and for investment decision making.
F. Data	The wind generation and speed data, and weather data will be obtained from EuroWind (Europe), NEOpoint (Australia), and resources from South Africa. Wind speed data from wind atlas of South Africa https://www.wasaproject.info/ (use the CSIR download portal). Data will also be obtained from the reanalysis database https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=form
G. Tools	This research project will 1. employ econometric methods to analyse the data and investigate key determinants of wind energy generation and how these affect pricing of wind derivatives products. 2. develop suitable mathematical models to capture key characteristics of wind derivatives markets; 3. use optimization-based calibration methods to fit these models to market data, to assess pricing performance, and 4. investigate risk mitigation and investment strategies. Matlab's "fmincon" routine will be used to search for the minimal point of the objective function. The ODEs in equations for the classical model will be solved by Matlab's "ode45".
TWO	Two key questions
H. What's new?	Wind derivatives are relatively new products (traded for first time in 2016 in EEX) and the fast transition to cleaner energy sources brings a fast-growing interest in effective modelling and evaluation for such products. Most existing studies are based in European markets. African and Australian energy markets operate differently, thus a comparison between different markets would be beneficial. Wind generation in Australia is leading globally, while wind generation in South Africa is emerging. The study proposes new modelling approaches having the potential to provide improved pricing and hedging performance. This will be the first study to apply advanced modelling frameworks (rough stochastic volatility models), which are typically used for financial markets, to renewable energy markets.
I. So what?	The research will bridge the gap between the variable nature of wind energy production and the need for stable, robust, manageable, and consistent models for pricing and risk management of renewable energy markets in Australia, Europe and Africa. By combining expertise from fields such as meteorology, finance, and energy economics, the study proposes an interdisciplinary approach to addressing challenges in renewable energy adoption and financial risk management. It strives to offer practical solutions that benefit stakeholders across the renewable energy sector, financial markets, and beyond. Also, this research addresses current industry and policy problems associated with decarbonization of the energy sector, thus the outcome would offer significant benefits for electricity market design and policy.

(*continued on next page*)

A.2. Evolution of our research plan

The approved pitch is a general pitch for a project on pricing wind energy derivatives in a very broad sense. Note that in the pitch we did not specify the required building blocks, or appropriate models to tackle this research question. In the report, we specify

Table A.1 (*continued*).

Research team	Dr. Mesias Alfeus; Dr. Muthe Mwampashi; Assoc. Prof. Christina Nikitopoulos; Professor Ludger Overbeck
ONE	One bottom line
J. Contribution	The contribution of this paper lies in the creation of novel approaches to evaluate energy derivative products, in particular wind derivatives, its interdisciplinary approach to modelling and analysis, its insights into risk management and investment strategies, and its potential to influence policy, market efficiency, and sustainability in the renewable energy sector. The impact of this paper extends to multiple sectors, fostering sustainable energy adoption, financial market innovation, informed decision-making, and environmental conservation.
K. Other Considerations	Target Journal: The target journal is the PBFJ (Impact Factor 4.6). Risk: Low. The research data for this project is readily available from the identified databases. The statistical and mathematical methodologies are within the expertise of the team members and have been used by the authors in previous research projects related to financial and commodity derivative instruments. Scope: To be successful in the PBFJ pre-registration publication initiative of Faff (2023).

the building blocks for wind derivatives pricing and the methods required to address the research question. The key building block for wind derivatives pricing is the WCU (WCU) and its forecasting. Thus, we focus on understanding the empirical features of the WCU in order to accurately model it, and on performing a forecasting analysis.

Furthermore, in the approved pitch, our objective was to consider three wind power markets, the German, the Australian (NEM), and the South African. We could include all three power markets, but we released that the Australian wind power market is a very interesting laboratory as it consists of five interconnected energy-only markets (in each of the five states). Thus, in the report, we propose to concentrate only in the NEM. There are several studies in the German markets (yet with different models), and the South African market is not sufficiently developed.

With regard to the key references motivating this research, note that this is a rapidly evolving research field with many recent contributions because of the critical importance of the energy transition in recent years. Benth and Benth (2009) was one of the first studies to explore the pricing of wind power derivatives. However, there is recent literature as well as recent developments on the design of these financial products, for example, the underlying asset of wind derivatives is typically the wind capacity utilization, and not the wind speed (which it used to be several years ago). These updates have informed the objective of our project and the proposed modelling approaches. Consequently, we have updated the key papers that motivate our project and include more recent works such as (Benth et al., 2021).

A.3.

Nomenclature

AEMO	Australian Energy Market Operator
AIC	Akaike Information Criterion
CFDs	Contracts for Difference
COF	change-of-frequency
f-OU	fractional Ornstein–Uhlenbeck
FiPs	Feed-in Premiums
FiTs	Feed-in Tariffs
Levy-OU	Lévy-driven Ornstein–Uhlenbeck
MRET	Mandatory Renewable Energy Target
MSE	Mean Squared Error
MW	megawatts
NEM	National Electricity Market
NSW	New South Wales
PBFJ	Pacific-Basin Finance Journal
PPAs	power purchase agreements
QLD	Queensland
RET	Renewable Energy Target
RMSE	Mean Squared Error
SA	South Australia
TAS	Tasmania
VIC	Victoria
VRE	variable renewable energy
WCU	wind capacity utilization

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