DEPARTMENT OF
MATHEMATICS

HEDGING RENEWABLES ENERGY GENERATION

MANAGING GROWING SHARE OF RENEWABLES PRODUCTION RISK AND ITS FINANCIAL IMPLICATIONS

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Master/BSc in Mechanical Engineering

Thesis Plan
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Acronyms

BSTS Bayesian Structural Time Series *(p. 10)*

CCGT Combined Cycle Gas Turbine *(p. 2)*
CCS Carbon Capture and Storage *(p. 2)*

ECMWF European Centre for Medium-Range Weather Forecasts *(p. 7)*
EEX European Energy Exchange *(p. 6)*

LCOE Levelized Cost of Electricity *(p. 2)*

MBSTS Multivariate Bayesian Structural Time Series *(pp. 10, 11)*
MCMC Markov chain Monte Carlo *(p. 13)*

PPA power purchase agreement *(p. 2)*

RES Renewable Energy Sources *(pp. 1–3, 8)*

1 Introduction

The growing share of renewables in the energy mix is introducing significant challenges for market participants along the value chain in power markets [9]. This thesis plans to study, from an energy management point of view, a Renewable Energy Sources (RES) portfolio, focusing on the stochastic production risks and the evaluation of hedging strategies to reduce market exposer and increase predictability and steady revenue streams. The performance of existing derivatives as hedges, explores the potential of quantity-related weather contracts proposed by major energy exchanges will be a critical focus of this thesis. Additionally, it will examine the evolving role of price-related derivatives as key hedging instruments, considering the significant influence of renewables on wholesale market prices.

The increasing proportion of renewable sources in energy production is leading to heightened volatility and creating doubts about the sustainability of consistent and steady revenue streams. This is due to the fact that renewable energy sources, like wind and solar power generation, are reliant on weather conditions and therefore do not serve as load-serving utilities. As a result, electricity production from these sources needs to be balanced by storage technologies to provide flexibility to the system and enhance reliability. Long-term energy storage is made mainly possible by pumped hydroelectric power plants. Furthermore, these are limited as they require specific geographical conditions, and most of the viable available sites have already been used. Short-term energy storage is made possible by batteries, which are still expensive and have limited capacity. Nonetheless, the cost of batteries is expected to decrease significantly in the coming years [5, 18]. The rise of renewable energy presents an incredible opportunity for investors, businesses, and governments to drive sustainable development and combat climate change. However, the increasing penetration of variable renewable energy can lead to more extreme spot prices and the need to increase the market's resilience.

1.1 Renewable Generation Costs

The analysis of the Levelized Cost of Electricity (LCOE) for various power generation technologies in Europe in 2023 indicates that onshore wind and utility-scale solar are the cheapest technologies to deploy. In 2023, onshore wind and PV have average LCOE of €63/MWh and €51/MWh, respectively. These values are projected to be more than halve in real terms by 2050 to €28/MWh and €24/MWh, making them the most cost-competitive options in the long term [1]. The report also suggests that carbon-capture thermal generation, specifically Combined Cycle Gas Turbine (CCGT) with Carbon Capture and Storage (CCS), is the cheapest non-nuclear, zero-carbon thermal generation. However, onshore wind is the most appealing technology in terms of wholesale revenue and LCOE in all 15 markets analysed. Therefore, based on the analysis, onshore wind and utility-scale solar appear to be the best long-term cheapest technologies for power generation in Europe.

1.2 Hedging RES Generation

The increasing share of renewables in the energy mix, particularly for wind and solar generation, is transforming the landscape of power markets. Introducing new challenges for market participants and requiring innovative solutions to manage uncertainty and production risks and maintain certain revenue streams. This thesis aims to contribute to the understanding of these challenges and potential solutions to manage generation risk by hedging the financial outcome of a RES portfolio.

The thesis will also explore the potential of existing derivatives as hedges, and the potential of quantity-related weather contracts proposed by major energy exchanges. Additionally, it will examine the evolving role of price-related derivatives as key hedging instruments, considering the significant influence of renewables on wholesale market prices.

In the diagram below, see figure 1.1, we present a high-level overview of the hedged discounted cash flow models that will be explored in this thesis.

One main contribution of this thesis is to provide a comprehensive analysis of the potential of hedging strategies, particularly on wind and solar (volume) generation, and the evaluation of the impact of these sources on the power market. In terms of price hedges, the most common instruments are through power purchase agreement (PPA), but the combination of both volumetric prices hedge is still relatively unexplored.

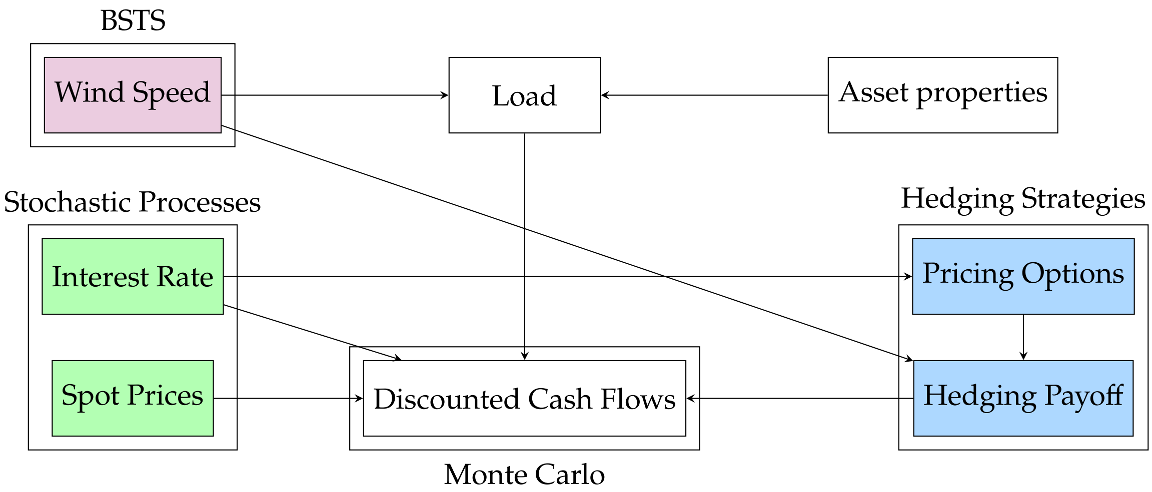

Figure 1.1: Hedged Discounted Cash Flow Models.

1.3 Conclusion

In conclusion, the growing share of renewables in the energy mix, particularly for wind and solar generation, is transforming the landscape of power markets. Introducing new challenges for market participants and requiring innovative solutions to manage uncertainty and production risks and maintain certain revenue streams. This thesis aims to contribute to the understanding of these challenges and potential solutions to manage generation risk by hedging the financial outcome of a RES portfolio.

2

Weather Derivatives

2.1 Introduction

Weather plays a crucial role in the economy, affecting various industries such as energy producers, distributors, retailers, agriculture, and transportation. Extreme weather events and temperature volatility at high latitudes are increasingly impacting supply and demand in businesses, making hedging strategies and weather derivatives essential for managing weather-related risks. The first weather transaction was made in 1997 by Enron, which sold a weather swap to a natural gas company, Koch Industries. After a long thinking process, they found a way to transfer the weather risk to a willing counterparty[3].

In the field of risk management, two main types of weather risk could be defined[11]. The term "Non-catastrophic weather risk" pertains to weather events with a high likelihood of occurring and resulting in limited losses. On the other hand, "Catastrophic weather risk" is defined as the risk associated with weather-related catastrophes characterised by low probability but substantial losses. Hereinafter, this thesis will focus on the non-catastrophic weather risk, which is what concerns most energy market application.

2.2 Weather Risk

Weather risks, particularly temperature and wind fluctuations, have significant impacts on operational and financial decisions, as well as revenues in various industries. Some industries, such as energy, agriculture, retailing, travel, and transportation, are more vulnerable to weather risks, which can affect both revenues and costs or both. In the table 2.1, it is possible to see the main weather risks for some important industries. As for the focal point of this thesis, the energy producers can be affected by temperature, wind, and solar irradiance and precipitation[7]. Weather risks can also affect the financial markets, as they can lead to increased volatility in commodity prices.

Industry	Weather Type	Risk
Energy Consumer	Temperature	Excessive or reduced demand
Energy Producer	Temperature, Wind, Solar irradiance, Precipitation	Excessive or reduced demand
Agriculture	Temperature, Precipitation	Crop yield, handling, storage, pests
Retailing	Temperature, Precipitation	Reduced demand
Travel	Temperature, Precipitation, Snowfall	Cancellations or lower revenue
Construction	Temperature, Precipitation, Snowfall	Delays, Higher budget costs

Table 2.1: Weather Risks

2.3 Weather Derivatives

Weather derivatives present various advantages over alternative weather risk management tools by efficiently transferring weather-related risks to parties capable of managing or utilising them effectively. These instruments have underlying variables like rainfall, temperature, humidity, wind speed, snowfall and are similar to conventional contingent claims that depend on the price of some fundamental. In the energy market, particularly taking into account the focus of this work, they can be used as a significant alternative to insurance contracts. The main advantages of weather derivatives are [7]:

1. Transfer weather related risks to the party which could manage or use them more eficiently;
2. Lower contracting costs due to reduced moral hazard and adverse counterparty risks in trading
3. Provide compensation for losses occurred;
4. Offer a payment simply based on weather index value (the field inspection is not needed any more);
5. Eliminate the insurable interest in the subject of insurance;
6. More convenient means to safeguard against limited losses associated with high-probability events

7. Be relatively easier hedged since weather risk is primarily volume risk and not price/market risk.

These benefits make it natural for industries to employ weather derivatives to stabilize revenues, cover over-budget costs, and reimburse losses [12]. Moreover, the limited correlation of underlying indices in weather derivatives with other financial indices positions them as an alternative asset class, contributing to portfolio diversification. The ability of weather derivatives to serve as both risk management tools and alternative assets underscores their versatility and relevance in diverse financial contexts.

The market for weather derivatives is expanding, where the energy sector has been a primary driver of the growth, with temperature-dependent derivatives being the most prevalent [2]. With the increasing penetration of renewable energy sources in the energy mix becoming the main source of energy, the role of weather derivatives in hedging against weather-related risks will become increasingly important.

2.4 Wind Futures

Despite being in a nascent stage, wind futures have already found their place in the energy market. The US Futures Exchange index served as the standard for settling wind derivatives up until 2008, utilizing the Nordix Wind Speed index as a measure [4]. This index was measuring the daily wind speed deviations from the 20 years mean. It had a benchmark at 100, and the deviations are aggregated over a measurement period, which typically is a month. More specifically, let the 20 years mean wind speed on day s be denoted by $\omega_{20}(s)$. The Nordix Index over a measurement period from τ_1 to τ_2 is then defined as

$$N(\tau_1, \tau_2) = 100 + \sum_{s=\tau_1}^{\tau_2} W(s) - \omega_{20}(s) \tag{2.1}$$

In recent developments, future contracts associated with wind power have been introduced by NASDAQ and the European Energy Exchange (EEX). The tracking of these wind indices differs from the Nordix Index approach in that they are founded upon the total production of wind power. These particular contracts are often referred to as the wind utilisation index. They are designed to remunerate the contract holder in the event the value of the index surpasses or falls below a predetermined level of production, corresponding to the futures market price [13]. The EEX futures contracts, in particular, utilise an underlying index predicated on the average yield of wind energy produced by German or Austrian power plants during predetermined time intervals [17]. Meanwhile, NASDAQ employs the NAREX WIDE index which is the NASDAQ Renewable Index Wind for Germany (DE) that relies on reanalyzed weather data for all the European Centre for Medium-Range Weather Forecasts (ECMWF) grid points within Germany.

2.5 Conclusion

In conclusion, weather related derivatives are being employed more frequently in alternative risk portfolios with multiple asset classes, particularly in the energy sector. By using weather derivatives, renewable energy producers can better manage weather-related risks, ensuring more stable revenues and reducing the overall risk of their businesses. As the use of renewable energy sources continues to grow, the role of weather derivatives in hedging against weather-related risks will become increasingly important.

3

Wind Power Generation

This thesis aims to study the volumetric risk effect induced by the intermittent nature of wind power generation, required to satisfy at a given time. Using whether derivatives is possible to develop hedging strategies to mitigate the volumetric risk, allowing to reduce the uncertainty and stabilise revenues from Renewable Energy Sources (RES).

3.1 Wind Power

The generation of wind power is intrinsically dependent on the velocity of wind. The symbiotic relationship between wind speed and the consequent energy production can be represented through the utilisation of turbine power curves. These curves provide a quantitative method to determine the power output of a wind turbine corresponding to a particular wind speed.

Crucially, the power curve is associated with two significant thresholds of wind speed. The thresholds are defined using the Betz law, which indicates the maximum power that can be extracted from the wind, independent of the design of a wind turbine in open flow. The first one is identified as the cut-in value, below which the turbine blades fail to generate power. This is due to the insufficient kinetic energy present in the wind to instigate their motion. Conversely, exceeding the second threshold, known as the cut-out value, leads to the safeguarding mechanism activating to prevent any potential structural damage to the system.

In practice, turbine manufactors provide a table of values for the power output at discrete wind speeds. Within the range of these two critical thresholds, the relationship between wind speed and the generated energy can be represented by a polynomial relationship interpolating manufactor data for each turbine model. See below 3.1, example for a 2MW turbine.

$$PC(x) = \begin{cases} 0 & \text{if } 0 < x < 4 \\ 21.78x^2 - 147.96x + 243.42 & \text{if } 4 \leq x \leq 13 \\ 2000 & \text{if } 13 < x \leq 25 \\ 0 & \text{if } x > 25 \end{cases} \quad (3.1)$$

To properly model power generation, the wind speed data, usually taken at reference height, must be adjusted to the given hub operation level of the turbine. The physical law that permits the conversion of wind intensity with respect to the altitude is:

$$v_h = v_{h_0} \cdot \left(\frac{h}{h_0}\right)^{\theta} \text{ with } \theta = \left(\ln \frac{h}{z_0}\right)^{-1} \quad (3.2)$$

Where v_h represents the wind speed measured at the height h of the wind turbine hub and v_{h_0} is the known value of the wind speed at the specified height data is recorded. Additionally, the parameter $z0$ is intimately connected to the site's morphological aspects wherein our postulated wind turbine is positioned. For instance, in the absence of any physical structures like buildings or trees, the value of this parameter typically falls within the range of 0.01 to 0.001. For situations involving offshore installations, the parameter is fixed at 0.0001, whereas an average value of $z0 = 0.005$ is employed for an onshore implementation.

As described, seven parameters are required to fully define the power curve of a wind turbine.

1. The cut-in wind speed, v_{cut-in}, below which the turbine is unable to generate power.
2. The cut-out wind speed, $v_{cut-out}$, above which the turbine is unable to generate power.
3. The rated wind speed, v_{rated}, at which the turbine is able to generate its maximum power.
4. The rated power, P_{rated}, which is the maximum power output of the turbine.
5. The power curve provided by the manufactor, which will determine the production between the threshold.
6. The hub height, h, at which the wind power is generated.
7. The spacial factor to diferentiate turbine surroundings.

3.2 Wind Generation Modelling

The focus of this section is to model wind power generation based on historical real and forecasted data. Conventional assumptions, like data independence and identically distribution, fall short when handling time-stamped data streams influenced by multifaceted predictors or features. This challenge necessitates the application of time series models to capture the inherent temporal dependencies, such as those stemming from macroeconomic indicators, enterprise operation, market dynamics and weather conditions.

One interest of this thesis is to explore recent techniques that work well for feature selection problems in time series applications. A technique that can join Bayesian inference with time series models is the Bayesian Structural Time Series (BSTS). Initially introduced and further explored by Scott and Varian [15, 16], the BSTS model is a powerful tool for feature selection, time series forecasting and inferring causal relationships.

Structural time series models are a class of state space models that decompose a time series into several components of interest. They have a considerable intuitive appeal, particularly for economic and social times. Furthermore, they provide a clear link with regressions' models, both in their technical formulation and in the model selection methodology that they employ [10].

The key to handling structural time series models is the state space representation, with the state of the system representing the unobserved components of the time series, such as trends and seasonal effects. Once in the state space, the Kalman filter plays a fundamental role as it recursively computes the predictive distribution of the state variables, given the observations up to that point in time.

Initially introduced by Jammalamadaka et al. [14], the BSTS can be extended to a multivariate time series model, which is particularly useful for the analysis of multiple time series that are related to each other. The Multivariate Bayesian Structural Time Series (MBSTS) can be used to explicitly model the correlations between different asset returns in a portfolio through the covariance structure specified by Σ_t, see equation 3.3.

3.2.1 The MBSTS model

Models of structural time series, exemplified by the MBSTS, are categorized under state space models tailored for time series data. They are represented by the ensuing equations:

$$y_t = Z_t \alpha_t + \varepsilon_t, \qquad \varepsilon_t \sim N_m(0, \Sigma_t) \tag{3.3}$$

$$\alpha_{t+1} = T_t \alpha_t + R_t \eta_t, \qquad \eta_t \sim N_q(0, Q_t) \tag{3.4}$$

Equation 3.3 is the observation equation, which relates the $m \times 1$ vector of observations at time t y_t to the $d \times 1$ unobserved latent states α_t, where d is the total number of latent states. The $m \times p$ matrix of coefficients Z_t links the unobserved factors and regressions' effects with the observations' vector y_t. The $m \times 1$ is the vector of observation disturbances ε_t and are assumed to have zero means and represented by a variance-covariance matrix Σ_t of the order $m \times m$.

The second equation 3.4 is the transition equation, which describes the evolution of the state vector α_t over time, characterised by the $d \times d$ transition matrix T_t. The $d \times q$ matrix of coefficients R_t is often referred to as the control matrix. The matrix η_t is an $q \times 1$ error vector, with a state diffusion matrix Q_t of the order $q \times q$, where $q \leq d$. In many standard cases, $q = d$ and Q_t is the identity matrix I_d. Although matrix Q_t can be specified freely, it is often composed of a selection from the q columns of the identity matrix I_d [6].

In summary, the MBSTS model is defined by the following set of parameters:

- y_t $(m \times 1)$: Observations at time t
- α_t $(d \times 1)$: Unobserved latent states d
- Z_t $(m \times p)$: Coefficients linking the unobserved factors and regression effects with the observations vector y_t
- ε_t $(m \times 1)$: Observation disturbances, assumed to have zero means, represented by the variance-covariance matrix Σ_t
- T_t $(d \times d)$: Transition matrix characterizing the evolution of the state vector α_t
- R_t $(d \times q)$: Control matrix of coefficients
- η_t $(q \times 1)$: Error vector with a state diffusion matrix Q_t of the order $q \times q$ where $q \leq d$
- Σ_t $(m \times m)$: Covariance matrix of the order $m \times m$ representing the observation disturbances
- Q_t $(q \times q)$: State diffusion matrix

As per developed by Harvey [10], a basic structural time series model can be represented by a direct interpretation of its underlying components. In a general, the model can be expressed as:

$$y_t = \mu_t + \theta t + \omega_t + \xi_t + \varepsilon_t, \qquad \varepsilon_t \sim N_m(0, \Sigma_\varepsilon), \quad t = 1, 2, ..., n \tag{3.5}$$

where y_t, μ_t, θt, ω_t, ξ_t and ε_t are m-dimension vectors, representing targeted time series, linear trend, seasonal, cyclical and regression components with the observation disturbances respectively. For simplicity, Σ_ε is a $m \times m$, positive definite matrix and assumed to be constant over time.

Elucidating further on the state space form, α_t aggregates these multifaceted components, depicting the concealed and unobserved latent states, such that:

$$\alpha_t = [\mu_t, \theta_t, \omega_t, \xi_t]^T \tag{3.6}$$

In the prevailing model, each component of the state is compiled individually, where every component produces an incremental influence on y_t. The adaptability of this model facilitates the incorporation of various model elements specific to each target series.

3.2.2 State Components

A structural time series model is composed of several components, each representing a distinct aspect of the time series, allowing to add flexibility and contributing to the overall model's predictive capabilities. The model components are typically divided into four main categories: trend, seasonal, cyclical and regression components. In the current model formulation, components are modelled explicitly and are assembled independently, with each yielding an additive contribution to y_t.

3.2.2.1 Trend Component

The trend component is a fundamental element of the structural time series model. It represents the long-term movement of the time series, capturing the underlying growth or decline over time. The trend component is typically modelled as a linear or non-linear function of time. The linear trend component is defined as:

$$\boldsymbol{\mu}_{t+1} = \boldsymbol{\mu}_t + \boldsymbol{\delta}_t + \boldsymbol{u}_t, \qquad \boldsymbol{u}_t \overset{iid}{\sim} N_m(0, \boldsymbol{\Sigma}_\mu) \tag{3.7}$$

$$\boldsymbol{\delta}_{t+1} = \boldsymbol{d} + \boldsymbol{P}(\boldsymbol{\delta}_t - \boldsymbol{d}) + \boldsymbol{v}_t, \qquad \boldsymbol{v}_t \overset{iid}{\sim} N_m(0, \boldsymbol{\Sigma}_\delta) \tag{3.8}$$

where:

- $\boldsymbol{\mu}_t$ $(m \times 1)$: trend component at time t
- $\boldsymbol{\delta}_t$ $(m \times 1)$: expected increase between time t and $t+1$
- $\boldsymbol{u}_t$ $(m \times 1)$: trend disturbance at time t
- $\boldsymbol{d}$ $(m \times 1)$: can be considered and the long-term trend

- $\boldsymbol{P}$ $(m \times m)$: diagonal matrix representing learning rate at which local trend is updated
- $\boldsymbol{v}_t$ $(m \times 1)$: is the trend disturbance at time t
- $\boldsymbol{\Sigma}_\mu$ $(m \times m)$: variance of the trend disturbance
- $\boldsymbol{\Sigma}_\delta$ $(m \times m)$: variance of the trend increment

The model features a parameter, $\boldsymbol{P}$ a diagonal matrix comprised by $(0 < P_{ii} < 1)$ for $i = 1, 2, \ldots, m$. It represents the learning rate that underlies the local trend update process providing the ability to balance short-term and long-term information. Specifically, when $P_{ii} = 1$, the model induces a random walk within the associated slope, leading to a non-stationary trend component.

3.2.2.2 Sesonality

The seasonal component is a crucial element of the structural time series model. A frequent used model [14] is:

$$\boldsymbol{\tau}_{t+1} = -\sum_{k=0}^{S_i-2} \boldsymbol{\tau}_{t-k}^{(i)} + \boldsymbol{w}_t^{(i)}, \qquad \boldsymbol{w}_t = [w_t^{(1)}, \ldots, w_t^{(m)}]^T \overset{iid}{\sim} N_m(0, \boldsymbol{\Sigma}_\tau) \tag{3.9}$$

3.2.3 Generatate Wind Series Forecast Scenarios

As conventional in Bayesian data analysis, predictions are derived from our model's posterior predictive distribution. This is achieved by drawing samples of model parameters and unseen or hidden states from their respective posterior distribution. Therefore, the posterior predictive distribution of $\hat{Y}$, representing the collection of forecasted values, can be described as:

$$p(\hat{Y}|Y) = \int p(\hat{Y}|\psi)p(\psi|Y)d\psi \tag{3.10}$$

Where Y is the observed data and ψ is the set of all the model parameters and latent states randomly drawn from $p(\psi|Y)$.

The posterior distribution of the model parameters can be trained by using Markov chain Monte Carlo (MCMC) algorithms. Taking advantage of working in the state space methods, forecast can be obtained continuing the Kalman filter after the last observation in the time series. This is known as the one-step-ahead forecast [8].

It is important to note that in this model, the predictive probability density is not contingent on parameter estimates, nor on the inclusion or exclusion of predictors with stationary regression coefficients these have all been fully integrated. The Bayesian model averaging ensures that we do not unduly commit to any specific set of covariates, thus helping us avoid an arbitrary selection, and neither do we settle for point estimates of their coefficients, thereby preventing overfitting.

The correlations amongst multiple target series are naturally accounted for when sampling for prediction values. The posterior predictive density is designed as a joint distribution over all predicted target series rather than a mere collection of univariate distributions. This methodology enables to project multiple target series in a comprehensive manner rather than examining each individually, as disjoint segments [14].

This can be particularly beneficial when generating summary statistics, such as the mean and variance-covariance, derived from the joint empirical distribution of forecast values.

3.3 Capacity Factor

Within the scope of this thesis, the capacity utilisation factor, also known as the capacity factor, we be employed as an indicator of a power production asset's performance capabilities. This factor represents an asset's actual output over a determined period compared to its potential output if it were possible for it to operate at full capacity continuously over the same timeframe. A higher capacity factor effectively signifies a more efficient energy production. When the mechanisms of energy trading are articulated, this factor can be converted directly into projected revenue, thus providing a tangible correlation between an asset's performance and its financial implications.

As previously mentioned, in chapter 2.4, the capacity factor is the metric that indexes, such as NASDAQ WIDE, adopted to model future wind contracts. Therefore, the portfolio capacity factor will be considered to model futures' contracts and evaluate the performance of the hedging strategies.

The capacity factor is calculated using the following equation:

$$cf_t = \frac{g_t}{C \cdot h_t} \tag{3.11}$$

Where g_t is the actual energy production, C is the nominal capacity production and h_t is the number of hours in the period t. The nominal capacity production refers to the maximum possible energy output under ideal conditions. The capacity factor is a dimensionless value, usually expressed as a percentage.

For T periods defined as $(t = 1, ..., T)$, the revenue R generated by a wind farm can be calculated as:

$$R = C\left(\sum_{t=1}^{T} h_t cf_t p_t\right) \tag{3.12}$$

Where p_t is the price of energy at time t. Energy agents typically have a multiple wind generators, where can be organised in different portfolios. Extending the previous definition, the revenue R generated by a wind portfolio composed by N assets, indexed by $i = 1, 2, ..., N$, where i can be a generation project or location. Let C_p be the portfolio's nominal production capacity, the revenue R_p generated by a wind portfolio can be calculated as:

$$R_p = \sum_{i=1}^{N} R_i \tag{3.13}$$

$$\Rightarrow C_p \left(\sum_{t=1}^{T} h_t cf_{tp} p_{tp} \right) = \sum_{i=1}^{N} C_i \left(\sum_{t=1}^{T} h_t cf_{it} p_{tp} \right) \tag{3.14}$$

where cf_{tp} is the portfolio's (weighted average) capacity factor at time t, R_i is the revenue generated by the asset i and cf_{it} is the ith-asset's capacity factor at time t. Dividing both sides by the portfolio's total capacity C_p:

$$\sum_{t=1}^{T} h_t cf_{tp} p_{tp} = \sum_{i=1}^{N} \frac{C_i}{C_p} \left(\sum_{t=1}^{T} h_t cf_{it} p_{tp} \right) \tag{3.15}$$

$$\Rightarrow \overline{R}_p = \sum_{i=1}^{N} x_i R_i \tag{3.16}$$

In this context, $\overline{R}_p$ denotes the revenue per megawatt (MW) of installed capacity and x_i elucidates the proportion of the total capacity of the portfolio denoted by asset i, which is also indicative of the weight of asset i in the portfolio. It is essential to note that, assuming the equivalence of prices for all assets integrated within the portfolio, equation 3.16 retains its validity across any given price p_{tp}.

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