# Designing Risk-free Service for Renewable Wind and Solar Resources

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**Abstract**

In all world geographies, renewable energy investment is viewed as a major component of the solution to meet the global energy demand. However, key renewable energy resources, such as wind and solar, are inherently stochastic, and thus, pose significant risk and reliability challenges. We apply financial engineering asset securitization principles in this paper to carve out risk-free generation capability from wind and solar energy generation. A market driven, dynamically evolving design and pricing of a risk-free tranche is developed that would allow renewable generators to competitively bid and participate in day-ahead power markets. We apply the framework to wind and solar resources located in different US geographies and assess the risk-free performance of the tranche against a risk-free benchmark established in this paper.

**Keywords**: renewable energy; risk mitigation; stochastic design; securitization; dynamic pricing.

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## 1 Introduction and Motivation

Environmental concerns are playing a critical role in pushing towards higher adoption and utilization of renewable energy (IRENA, 2017; Deloitte, 2022). Renewable generation has been the fastest growing resource in the U.S. (EIA, 2021), supported by federal tax credits and state-level renewable targets (Dewey and Nelson, 2020; EOEEA, 2020). However, the inherent stochasticity of renewable generation presents significant challenges for the power grids (Wan et al., 2015; Liang, 2016) and the renewable energy producers (Roulston et al., 2003; Orlov et al., 2020), which impedes their competitive participation in the power markets. An increasing renewable penetration therefore calls for developing risk management strategies for a seamless integration of renewable assets into power markets and in the functioning of power grids.

In this paper, we utilize asset securitization principles to define a risk-free offering based on stochastic renewable generation resources, which can be priced, offered and fulfilled comparable to their non-stochastic conventional generation counterparts. The risk-free tranche definition of securitization utilizes an assessment of generation risk profile of the renewable asset and dynamically adapts the attachment & detachment points of the risk-free tranche to the risk profile. We develop a minimum entropy risk-neutral pricing framework to determine the market-based bid curves for the risk-free tranche, and evaluate the performance of the risk-free tranche relative to a carefully defined risk-free benchmark for the day-ahead power markets. A comparably and reliably performing risk-free tranche can provide the necessary assurance to power grid system operators to incorporate the renewable assets based risk-free tranche in the typical day-ahead unit commitment and economic dispatch decisions.

Deregulation of power markets in the past decades has merited borrowing risk management principles from the financial domain to benefit the power markets (Bierbrauer et al., 2007; Pirrong and Jermakyan, 2008; Cartea and Villaplana, 2008). Derivative instruments are used extensively to hedge electricity price risk and develop strategies for power market participants (Vehviläinen and Keppo, 2003; Deng and Oren, 2006; Doege et al., 2009; Falbo et al., 2010; Coulon et al., 2013). Increasing renewable energy penetration, with greater dependence on weather elements, has supported the utilization of cross-hedging and weather derivatives based risk management strategies (Müller and Grandi, 2000; Bessembinder and Lemmon, 2002; Brockett et al., 2005; Pérez-González and Yun, 2013; Hain et al., 2018; Bhattacharya et al., 2020). While various financial risk management principles have been applied in the literature in the context of renewable energy assets, to the best of our knowledge asset securitization principles have not been utilized so far to craft reliable renewable generation offering for their seamless participation in the day-ahead power markets, which is critical to enable and sustain the growth of renewable generation.

In the credit markets, securitization has been used for decades for risk pooling and carving out securities to match investors' risk-reward appetite (Gupta, 2014). Securitization has been proposed for renewable energy for the possible benefit from securitizing cashflow of renewable assets for risk mitigation, access to a large capital pool, improvement in financing, reduction in transaction costs, and other growth opportunities (Liu et al., 2007; Krupa and Harvey, 2017; Alafita and Pearce, 2014; Gabig et al., 2015; Jiang and Chen, 2005; Lowder and Mendelsohn, 2013; Hyde and Komor, 2014). Our utilization of asset securitization principles for stochastic renewable generation resources is geared towards operational goals of allowing their active participation and integration in power markets and enhance their revenue generation capability.

Prior studies have developed optimal bidding strategies for renewable integrated micro-grids by modeling uncertainties in renewable energy production (Ferruzzi et al., 2016; Wang et al., 2017; Das and Basu, 2020; Nikpour et al., 2021). However, in the larger scale power grids, existing renewable risk management solutions and bidding strategies assume renewable generators to be price takers, which limits their competitiveness, revenue generation capability, as well as subjects them to high degrees of curtailment (Prokhorov and Dreisbach, 2022; Prol et al., 2020; Bird et al., 2016). These traits are not supportive of sustainable growth and investment in renewable energy. Existing literature has also not developed risk-responsive pricing strategies to support the stochastic renewable generators' bidding in the day-ahead power markets. The methodology developed in this study addresses this challenge by designing a risk-responsive definition and pricing for a risk-free offering based on renewable assets.

We develop a minimum entropy risk-neutral pricing framework to construct a bidding strategy for the risk-free tranche of a renewable asset (Avellaneda, 1998; Frittelli, 2000; Ssebugenyi et al., 2013; Dhaene et al., 2015). This market price driven framework utilizes contingent claims pricing based on the key determinants of day-ahead and real-time market prices and the parameters that define the risk-free tranche. The framework applied dynamically based on the generation risk profile of an asset leads to the construction of dynamic risk-free bid curves for the renewable asset for the day-ahead market. Research literature provides many studies identifying the key drivers of electricity market prices across various geographies (Girish and Vijayalakshmi, 2013; Kiesel and Paraschiv, 2017; Mosquera-López and Nursimulu, 2019; Zarnikau et al., 2019, 2020). Electricity demand (load) and natural gas price are the most important determinants for the day-ahead market prices, and these factors combined with day-ahead market prices are key determinants for the real-time market electricity prices.

Beyond defining and pricing the renewable energy risk-free tranche, its performance evaluation is critical for an assurance of comparability to conventional risk-free generation. This is required in terms of both assurance of delivery and financial reward to the renewable generator. The parametric choice that defines the risk-free tranche, which are called attachment-detachment points in securitization, is done to match assurance of delivery with a conventional risk-free benchmark. For evaluation of financial performance, we conduct a risk-reward comparison between a bidding strategy used by a conventional risk-free benchmark and that of the risk-free tranche developed in this paper. Sharpe ratio of daily return is used as the performance metric for this comparison, along with the tail risk characteristics of daily return. Since there is no established risk-free benchmark for the power markets, similar to short-term US Treasury rates for the capital markets, we define the risk-free benchmark in this paper based on a combined cycle natural gas-based power generator.

According to the Bipartisan Policy Center, natural gas is the largest source of electricity generation in the U.S. with a market share of 37% (Center, 2020), and it is projected to retain this status at least until 2050. Combined cycle natural gas generators are more stable, efficient and have higher flexibility compared to other conventional generators (Shahidehpour et al., 2005). For these reasons, a past study evaluates combined cycle natural gas generators as an ideal choice for a risk-free benchmark for the power markets (Hörnlein, 2019), especially relevant as power markets transition to higher renewable generation share. While no power generation asset is flexible and truly risk-free in the power markets, for the above reasons a combined cycle natural gas generator is a reasonable choice of a conventional risk-free benchmark.

We implement the risk-free tranche for many wind and solar generation resources at different locations in New York and Texas. The risk-free tranche is designed for these assets after analyzing their generation risk profiles and renewable bid curves are developed for the day-ahead markets. Both the definition of tranches and the bid curves respond to the productivity of the renewable resource at different times of the day and year, as well as the day-ahead and real-time market price dynamics. The Sharpe ratio performance of the risk-free tranche is quite comparable to that of our combined cycle natural gas-based risk-free benchmark asset. The tail risk characteristics of the risk-free tranche are practically negligible, supporting the risk-free nature of the tranche. Therefore, a comparably and reliably performing risk-free tranche provides the necessary assurance to power grid system operators to incorporate the renewable assets based risk-free tranche in the typical day-ahead unit commitment and economic dispatch decisions.

The rest of the paper is organized as follows. Section 2 provides a detailed description of the methodology for the design of the risk-free tranche, the pricing framework for the tranche to develop a day-ahead market bidding strategy. The section also outlines the development of the risk-free benchmark and presents the performance evaluation formulation for the risk free tranche. We describe the data and the data sources used in the study in Section 3, followed by Section 4 demonstrating the implemention of the risk-free tranche design and performance evaluation for a selection of renewable assets. Conclusions of the study and related discussion of future work are presented in Section 5.

## 2 Methodology to Design a Risk-free Tranche

Designing a risk-free tranche based on the throughput of a stochastic renewable energy resource requires assessing the risk profile of the resource's generation. Based on this risk profile, tranche attachment-detachment points or cutoffs needs to be determined and pricing of the tranche needs to be developed. Pricing to support the bidding strategy of the risk-free tranche will conduct a valuation of the risk underlying renewable generation and the contractual parameters of the risk-free tranche. We describe each element of the methodology for the design of the risk-free tranche, followed by the framework developed to evaluate its performance.

### 2.1 Risk-free Tranche Definition

Generation risk profile of a renewable asset varies by the hour of the day and day of the month or year. Moreover, the day-ahead market seeks bids for hourly delivery of power generated from all bidding resources. Therefore, for the definition of the risk-free tranche, the attachment-detachment points of the tranche need to be determined for each hour of each day. The attachment-detachment points are statistical percentiles of the hourly generation distribution of a renewable asset to ensure the tranche is delivered at the required assurance. The attachment point of the risk-free tranche is guided by a low enough percentile of the generation distribution that ensures high level of reliability matched with that of conventional generators, such as, a combined cycle natural gas generator.

The attachment point of the risk-free tranche is identified by examining the reliability of the risk-free benchmark defined in terms of a combined cycle (CC) natural gas generator. Contemporary CC generators have an average 96% reliability rate, implying that they fail to deliver on their contractual obligation in the day-ahead market only 4% of the times they bid (Kehlhofer et al., 2009). We match the reliability of the risk-free benchmark by taking the attachment point of the risk-free tranche as the $4^{th}$ percentile of the renewable asset's generation distribution for each hour. This implies that the risk-free tranche will deliver at a matched reliability of 96%.

We need to define the detachment point at the other end of the risk-free tranche definition, with the acknowledgment that every percentile above the $4^{th}$ percentile exposes the tranche to incremental risk of failing to deliver. This additional risk is borne by the renewable generator and is priced into the bid curve. Higher the bid price, lower the likelihood the bid will be taken up by the market, thus reducing the revenue of the renewable generator. Therefore, the detachment point of the risk-free tranche is defined specific to each renewable resource with the aim of matching its risk-return characteristics with that of the risk-free benchmark. Therefore, the detachment point of the risk-free tranche is set at a low percentile, $5^{th}$, $6^{th}$, etc., that yields an overall reliability of 96% for the risk-free tranche, albeit at a higher price point with increasing percentiles above the $4^{th}$ percentile of the renewable asset's generation distribution.

This definition of the risk-free tranche facilitates the independent system operator to treat the risk-free tranche as equivalent to the reliable offering from other traditional generators, such as the combined cycle natural gas generators. However, one critical element of this definition of the risk-free tranche is a thorough evaluation of the hourly generation distribution of the renewable asset. Noting the high variability in renewable generation by the hour of the day and variation across days, we conduct a generation and forecast of generation assessment to define days of similar generation profile, called the *characteristic days*.

### 2.1.1 Characteristic Days

Power generation of renewable assets, such as solar and wind farms, is highly dependent on variations in the weather patterns. As noted above, this requires a different definition and bidding strategy for the risk-free tranche for each hour. Although no two days are identical by their exact generation levels, several days can be identified as similar by some key generation and forecast of generation characteristics. These similar days of a type, called *characteristic day*, can be treat as independent and identically distributed observations to allow percentile estimates for each hour's generation distribution for that characteristic day.

For identifying similar days for the generation of a renewable asset, each day is summarized by a set of key daily statistics for the asset's hourly generation and forecast of generation. These key daily statistics describe the mean, spread, maximum, minimum of the asset's daily generation and forecast of generation. These features are used to conduct a detailed clustering analysis using k-means clustering algorithm (MacQueen, 1967) to identify days of similar risk profile. The optimal choice of $k$ is identified for each renewable asset based on the inflection point in the k-means elbow curve. The centroid of each cluster typifies each characteristic day type, and the risk-free tranche definition and bidding strategy for each renewable asset is developed for each hour of each characteristic day type.

## 2.2 Risk-free Tranche Pricing

We assume the day-ahead bids are cleared for all hours of the next day by the independent system operator at time, $t$, where the bids are placed by all the generators at time, $t-\delta$. The bid timeline is shown in Figure 1. Let the actual generation from the renewable asset at time $t+1$ be $Y_{t+1}$ and the day-ahead (forward) price of electricity at market clearing at $t$ be $D_t$, where as the real-time (spot) price when the contract is delivered is $R_{t+1}$. The information available to the renewable generator at the time of risk-free tranche pricing and bid curve determination is the natural gas price, $N_{t-1}$, electricity load at the relevant node of the grid for the renewable asset, $L_{t-1}$, and historical time series of generation, $Y_{t-i}, i \geq 1$ and forecast error, $F^e_{t-i}, i \geq 1$.

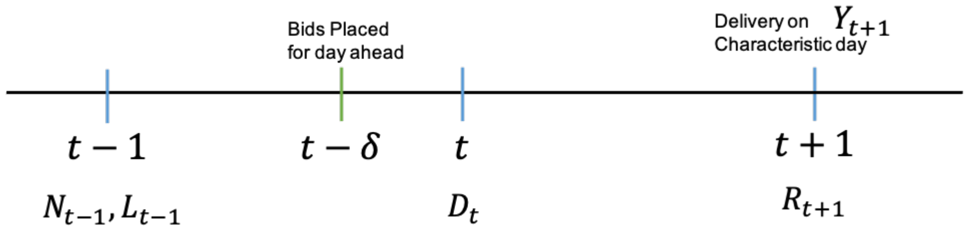


Figure 1: Timeline for placing bids in the day ahead markets

Valuation of the risk underlying the range of renewable generation (MW) offered under the risk-free tranche's attachment-detachment points utilizes risk-neutral valuation of contingent claims. Each percentile point, $C_j, j = 1 \ldots J$, in the attachment-detachment range is valued as a contingent claim, responsive to the increasing risk at the incremental percentile level. As described earlier, $C_1$ is the $4^{th}$ percentile of the generation distribution for time $t+1$ and the specific type of characteristic day and $C_J$ is the detachment point for the risk-free tranche. The contingent claim underlying each bid point, $C_j$, is given as,

$$
\begin{aligned}
Z_{j,t+1} &= D_t, Y_{t+1} \geq C_j, && (1) \\
&= -R_{t+1}, Y_{t+1} < C_j, && (2)
\end{aligned}
$$

where in the scenario $Y_{t+1} \geq C_j$, the renewable generator meets its delivery obligation up to that bid point and receives a payment of $D_t$ per MW, while in the scenario $Y_{t+1} < C_j$, the renewable generator must pay the real-time price, $R_{t+1}$, per MW to make up for the shortfall in generation. In a risk-free tranche, a renewable generator must bear the risk of generation shortfall and resulting real-time price risk exposure, therefore valuation of this risk must be built into the bid price. Therefore, risk-neutral contingent claims pricing used for each bid point, $C_j$, is constructed as follows.

$$
\begin{aligned}
\boldsymbol{P_{rf,j}} &= \eta_{rf} * E[D_t | Y_{t+1} \geq C_j] * P(Y_{t+1} \geq C_j) + && (3) \\
& \quad E[E^Q[R_{t+1}] + \lambda_{rf} * \sigma^Q[R_{t+1}] | Y_{t+1} < C_j] * P(Y_{t+1} < C_j),
\end{aligned}
$$

where $j = 1, \ldots, J$. The first of the two components above reflects the scenario where generation exceeds bid percentile and the price point associated with this scenario is the expected day-ahead price, $E[D_t | Y_{t+1} \geq C_j] * P(Y_{t+1} \geq C_j)$, along with a discount loading, $\eta_{rf}$, for allowing competitive bids. The second term corresponds to the scenario when the generation fails to exceed the day-ahead commitment, when the renewable generator must acquire the shortfall from the real-time market (or incur real-time price penalty) to honor its day-ahead obligation. The valuation implication is captured by $E[E^Q[R_{t+1}] + \lambda_{rf} * \sigma^Q[R_{t+1}]|Y_{t+1} < C_j] * P(Y_{t+1} < C_j)$, where $E^Q[R_{t+1}]$ is the average price exposure and $\lambda_{rf}\sigma^Q[R_{t+1}]$ captures the price of risk exposure in terms of renewable generator's risk aversion parameter, $\lambda_{rf}$.

The complete risk-free tranche bid curve is constructed by a linear interpolation between all bid price points, $\boldsymbol{P_{rf,j}}$, given in Equation 3 as follows:

$$f_{rf}(C_x) = \begin{cases} P_{rf,j} & C_x = C_j; j = 1, \ldots, J \\ P_{rf,j} + \frac{P_{rf,j+1} - P_{rf,j}}{C_{j+1} - C_j}(C_x - C_j) & C_{j+1} > C_x > C_j. \end{cases} \quad (4)$$

$C_x$ is the renewable generation in MW corresponding to $x^{th}$ percentile of generation distribution. $\boldsymbol{P_{rf,j}}$ is the bid price in \$/MW at the percentile bid points and $f_{rf}(C_x)$ is the complete bid curve from $C_1$ to $C_J$, attachment to detachment points of the risk-free tranche.

As seen in Equation 3, the bid curve valuation requires a reliable estimate of the expected day-ahead price, $E[D_t]$, and the distribution of the real-time market price, $R_{t+1}$. We discuss this in the next section. Additionally, the expectations in Equation 3, $E^Q[.]$, are taken with respect to a risk-neutral measure. We need to determine an appropriately constructed risk-neutral measure to implement the above risk-free tranche pricing and bid curve determination approach. For each characteristic day type, a bid curve using the above framework is developed for each hour, which reflects the characteristic days' generation risk profile.

### 2.2.1 Electricity Price Models

Based on the literature, we use regional demand for electricity (load) and natural gas price as the key components for estimating electricity prices. A regression model for the hourly day-ahead prices, $D_t$, is built using lagged regional load, $L_{t-1}$, and lagged natural gas prices, $N_{t-1}$. Similarly, a regression model is built for hourly real-time price, $R_{t+1}$, using estimated day-ahead price, $E[D_t]$, lagged regional load, $L_{t-1}$, and lagged natural gas price, $N_{t-1}$. The models are summarized as follows.

$$
\begin{aligned}
D_t &= \alpha L_{t-1} + \beta N_{t-1} + \epsilon, && (5)\\
E[D_t] &= \alpha L_{t-1} + \beta N_{t-1}, && (6)\\
R_{t+1} &= \gamma E[D_t] + \delta L_{t-1} + \theta N_{t-1} + \epsilon', && (7)
\end{aligned}
$$

where $\alpha, \beta, \gamma, \delta, \theta$ are the estimated regression coefficients and $\epsilon'$ is the residual error for real-time market price. The residual errors for the real-time market prices model are retained, which reflect other sources of risk such as transmission and outages, beyond the load, natural gas price and day-ahead price factors. Simulating from standard distributional fit on the residuals, $\epsilon'$, yields the variations in the real-time price in Equation 7. This variation is used to estimate the second term of Equation 3, namely $E[E^Q[R_{t+1}] + \lambda_{rf} * \sigma^Q[R_{t+1}] | Y_{t+1} < C_j] * P(Y_{t+1} < C_j)$, when the renewable generation fails to exceed the bid-point of the risk-free tranche.

### 2.2.2 Estimation of Risk Neutral Probabilities

The day-ahead price in the power markets is effectively the forward price for the spot or real-time market price, since it is fixed at $t$ for delivery of the product at $t+1$. Therefore, the forward price is an unbiased estimate of the future spot price, under an appropriately defined Martingale measure as per the electricity price expectation hypothesis (Eydeland and Wolyniec, 2002). This relationship between the real-time and day-ahead prices can be stated as,

$$D_t = E^Q[R_{t+1}], \tag{8}$$

where the expectation is taken with respect to an appropriate risk-neutral measure. On the basis of many states of the real-time market price and only one above relationship, it is not possible to identify a unique risk-neutral measure. In this incomplete market setting, we seek a minimum entropy risk-neutral measure that satisfies the above relationship between day-ahead and real-time electricity prices.

A minimal-entropy risk neutral probability measure, $\{q_i, i = 1, \ldots, n\}$, is obtained by minimizing the entropy difference between the physical probability measure, $\{p_i, i = 1, \ldots, n\}$, and the risk-neutral measure, $q_i$. Before we formulate the optimization problem to obtain this minimum entropy risk neutral measure, we restate Equation 3 as follows.

$$\begin{aligned}\boldsymbol{P_{rf,x}} = \eta_{rf} * E[D_t|Y_{t+1} &\geq C_j] * P(Y_{t+1} \geq C_j) + \\ E[E[D_t][E^Q[\frac{R_{t+1}}{E[D_t]}] &+ \lambda_{rf} * \sigma^Q[\frac{R_{t+1}}{E[D_t]}]]|Y_{t+1} < C_j] * P(Y_{t+1} < C_j).\end{aligned} \tag{9}$$

The above normalized re-statement of Equation 3 is done for tractability to avoid estimating risk-neutral probabilities, $\{q_i, i = 1, \ldots, n\}$, for each discrete unique value of $E[D_t]$.

We define $V_t = \frac{R_{t+1}}{D_t}$ to estimate the discretized risk neutral probabilities with $n$ states. The minimum entropy risk neutral probabilities are estimated by minimizing the distance between physical and risk neutral probabilities subject to constraints that enforce the relationship in Equation 8 between day-ahead and real-time market prices using the following optimization formulation:

$$\min \quad \sum_i^n (p_i - q_i)^2 \tag{10}$$

s.t.

$$\sum_{i=1}^n q_i = 1.0, \tag{11}$$

$$\sum_{i=1}^n q_i v_i = 1.0, \tag{12}$$

$$0 \leq q_i \leq 1. \tag{13}$$

In the above formulation, $\{v_i, i = 1, \ldots, n\}$ are the $n$ discretized points of the $V_t$ ratio and constraints in Equations 11-13 ensure $q$ to be a risk-neutral measure.

### 2.3 Evaluating Risk-free Tranche Performance

Beyond definition and pricing, it is essential to evaluate the performance of the risk-free tranche. As stated earlier, the performance of the risk-free tranche is important both in terms of reliability and financial characteristics. The choice of attachment and detachment points of the risk-free tranche matches the tranche in reliability with a combined cycle natural gas generation. Equation 3 entails that when the renewable generation fails to meet the committed offering, the real-time market is accessed to make up for the shortfall. However, making up for this shortfall has financial implications, therefore performance evaluation between risk-free tranche and risk-free benchmark is primarily financial.

The financial performance evaluation compares the risk-reward characteristics of the risk-free tranche against that of the risk-free benchmark. For this purpose, daily return time-series is developed for both the resources. Daily return is determined in terms of the daily revenue received based on the hourly bid curves of the resource and daily cost estimates, as $Return_x = \frac{Revenue_x - Cost_x}{Cost_x}$, where $x$ can be '$rf$' to depict risk-free tranche or $x$ is '$rfb$' to depict the risk-free benchmark. The daily revenue for both the resources is computed as:

$$\text{Revenue per day} = \sum_{\tau=1}^{24} D_t Q^e_{x,t} - \sum_{\tau=1}^{24} R_{t+1} I_{(Y_{t+1} < Q^e_{x,t})} (Q^e_{x,t} - Y_{t+1}), \tag{14}$$

where $D_t$ is the day-ahead market price, $R_{t+1}$ is the real-time market price at $t+1$, $Y_{t+1}$ is the resource's generation at $t+1$, $I$ is an indicator function, and $\tau$ is a count of 24 hours of a day.

The risk-free tranche bid curves developed in Equation 4 for each hour are used to determine the amount of power the renewable resource sells in the day-ahead market. The contracted power under the risk-free tranche, $Q^e_{rf,t}$, is a function of the risk-free bid curve, $f_{rf}$ as follows.

$$Q^e_{rf,t} = \begin{matrix} 0 & D_t < P_{rf,C_1}, \\ f_{rf}^{-1}(D_t) & P_{rf,C_1} \leq D_t \leq P_{rf,C_J}, \\ C_J & D_t > P_{rf,C_J}, \end{matrix} \tag{15}$$

where $C_1$ and $C_J$ are the attachment and detachment points, respectively, of the risk-free tranche and $P_{rf,C_j}$ is the bid price in \$/MW of the risk-free tranche corresponding to $C_j$, a percentile of the generation distribution.

The cost term of renewable asset is dominated by the fixed operations and maintenance (FOM) costs. The daily FOM cost is treated as the cost of goods sold, which is either scaled up or down based on the productivity of the type of characteristic day. The total cost is applied to the risk-free tranche proportional to the fraction of asset's generation allocated to the tranche under the assumption that renewable generation is curtailed at 60%ile of hourly generation distribution to control overall shortfalls. Therefore, daily cost allocated to the risk-free tranche is determined by the productivity of the tranche and is given by,

$$\text{Cost}_{rf} = \frac{\sum_{\tau=1}^{24} C_{J,\tau}}{\sum_{\tau=1}^{24} C_{60\%ile,\tau}} * F, \tag{16}$$

where $C_{J,\tau}$ is the detachment point of the risk-free tranche at hour $\tau$ of the day and $F$ is the fixed daily O&M cost of the renewable asset.

### 2.3.1 Risk-free Benchmark

The risk-reward characteristics of the risk-free benchmark, defined in terms of a combined cycle (CC) natural gas generator, is developed similarly in terms of its revenue and fixed & variable costs. The daily return of a combined-cycle natural gas generator is defined as before with $x$ replaced by '$rfb$' and daily revenue given by:

$$\text{Revenue}_{rfb} = \sum_{\tau=1}^{24} D_t * Q^e_{rfb,t} - \sum_{\tau=1}^{24} R_{t+1} * (1 - \rho_{t+1}) * Q^e_{rfb,t}, \tag{17}$$

where $\rho_{t+1} \in \{0, 1\}$ represents reliability metric simulated as a binary time series with $P(\rho_{t+1} = 1) = 0.96$ and the power contracted by the risk-free benchmark asset in the day-ahead market at time $t$ is given by:

$$Q^e_{rfb,t} = f^{-1}_{rfb}(D_t), \tag{18}$$

where $f_{rfb}$ is the risk-free benchmark assets hourly dynamic bid curve. The total daily cost for a CC unit is given by:

$$\text{Total Cost}_{rfb} = F + (\sum_{n=1}^{24} V * \rho_{t+1} * \ Q_{rfb,t}) + (H * N_t * \sum_{n=1}^{24} \rho_{t+1} * \ Q_{rfb,t}), \tag{19}$$

where $F$ and $V$ are the fixed and variable operations & maintenance costs, respectively, $H$ is the heat rate of a natural gas power plant, $N_t$ is the price of natural gas fuel, $Q_{rfb,t}$ is the power contracted in the day ahead market at time $t$, and $\rho_{t+1} \in \{0, 1\}$ is the reliability metric of a CC unit. Unlike the risk-free tranche, the bid curves of the risk-free benchmark are extracted from the bids data posted by various independent system operators, which will be discussed in the data section, Section 3.

### 2.3.2 Performance Evaluation Metric

Financial performance of risk-free tranche is compared against that of the risk-free benchmark in terms of Sharpe ratio. The daily return time series for both the resources are used to construct estimates of Sharpe ratio. The standard Sharpe ratio assumes zero volatility of the risk-free asset, however in the power markets setting, the risk-free benchmark doesn't have zero volatility, given that its reliability is 96%. We adjust the performance evaluation metric by comparing the risk-adjusted returns of the renewable asset's risk-free tranche, $\frac{R_i}{\sigma_i}$, against that of the risk-free benchmark, $\frac{R_f}{\sigma_f}$, where $R_i$ and $\sigma_i$ are the average daily return and standard deviation of daily return for the risk-free tranche, respectively, and $R_f$ and $\sigma_f$ are the corresponding values for the risk-free benchmark. Risk-free tranche performance in terms of this performance metric, for being comparable to the risk-free benchmark, should be similar to that of the risk-free benchmark.

# 3 Data for Design and Evaluation of Risk-free Tranche

Implementation of the methodology developed in Section 2 for the design and performance evaluation of a renewable generation based risk-free tranche requires several datasets. Data to support this study are extracted from two major sources, the independent system operators and the US Energy Information Administration (EIA). The first dataset is for renewable generation resources in disparate geographies to implement and assess the framework. Pricing formulation in support of developing risk-free tranche bidding strategies requires power markets price, load and natural gas price data. Finally, to accomplish performance evaluation, we need to define and implement the performance of the risk-free benchmark. Bidding and cost data for combined cycle natural gas generator are utilized for this purpose. We describe these datasets next.

## 3.1 Solar and Wind Resources Data

Renewable assets, constituting of wind and solar resources, generation and forecast time series data are needed and acquired from New York Independent System Operator (NYISO). We have acquired and implemented the methodology for a suite of wind and solar resources from the Texas geography also, however we will focus on the data and results in this paper based on New York state resources. Wind generation and forecast data, aggregated for 3 wind farms, are available for the time period Jan 2017- Dec 2020. Solar generation and forecast data from behind-the-meter (BTM) installations aggregated at the zonal level are available for the time period Jan 2018 - Dec 2019. The aggregated data from collocated units in a zone are treated as from a single renewable asset.

Wind and solar assets from New York-Zone A are chosen to demonstrate the design and performance evaluation of risk-free tranche. Wind and solar assets have an installed generation capacity of 135.5MW and 68.5MW, respectively. Table 1 shows the descriptive statistics of the hourly generation and forecast time series for the solar and wind renewable assets. The fixed operations and maintenance cost estimates are obtained for representative solar unit with 150MW generation capacity and a wind unit with 200MW generation capacity from EIA (2020). The cost estimates are scaled down proportionately as per the generation capacity of the renewable assets in our study.

| | Solar Generation | Solar Forecast | Wind Generation | Wind Forecast |
|---|---|---|---|---|
| count | 17500.00 | 17500.00 | 34705.00 | 34705.00 |
| mean | 7.85 | 7.66 | 29.68 | 30.12 |
| std | 13.32 | 12.31 | 29.55 | 28.86 |
| min | 0.00 | 0.00 | 0.00 | 0.00 |
| 25% | 0.00 | 0.00 | 5.10 | 6.00 |
| 50% | 0.05 | 0.18 | 19.90 | 20.80 |
| 75% | 10.18 | 11.11 | 46.70 | 47.60 |
| max | 62.01 | 68.35 | 125.00 | 124.90 |

Table 1: Descriptive stats of generation & forecast for the solar and the wind unit

### 3.2 Price Determinants Data

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Day-ahead and real-time market electricity prices & real time load data for New York - Zone A for the time period Jan 2013-Dec 2020 are obtained from New York Independent System Operator (NYISO). The zonal electricity prices and load data are publicly available from NYISO website. The Henry-Hub daily natural gas spot price data are obtained from the U.S. Energy Information Administration, which is also publicly available. Table 2 shows descriptive statistics for day-ahead price, real-time price, load data at hourly granularity and natural gas price at daily granularity.

### 3.3 Risk-free Benchmark Data

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Hourly bidding data for combined cycle natural gas generators is publicly available from NYISO website. Representative bid curves are constructed based on six combined cycle (CC) units from six different companies, four of these units are located in Zone J and two are in Zone G of New York state, which each bid into their respective zonal power markets. We extract the MW bid level and $/MW bid curves for each hour of each unit for the time period Oct 2019 to Sep 2020. The extreme CC bid levels are removed since these correspond to levels that the CC units intends to not fulfill

| | Real Time Price | Day Ahead Price | Load | Natural Gas Price |
|---|---|---|---|---|
| count | 70056.00 | 70056.00 | 70056.00 | 70056.00 |
| mean | 30.66 | 30.13 | 1765.06 | 3.00 |
| std | 41.75 | 24.29 | 247.87 | 0.85 |
| min | 0.00 | 1.03 | 790.28 | 1.33 |
| 25% | 15.41 | 17.54 | 1580.17 | 2.49 |
| 50% | 22.98 | 25.82 | 1757.85 | 2.88 |
| 75% | 32.69 | 35.78 | 1922.49 | 3.50 |
| max | 1237.21 | 500.00 | 2822.58 | 8.15 |

Table 2: Descriptive statistics of price determinants at hourly or daily granularity.

due to their upper operating limits. For the evaluation of performance of the risk-free benchmark, we additionally obtain day-ahead and real-time market prices for these zones from NYISO website.

Cost estimates for CC unit require fixed O&M cost, variable O&M cost, and heat-rate to convert natural gas fuel into electric power. These data are obtained from US EIA, where we focus specifically on a representative CC unit that has combustion turbine H class, combined-cycle single shaft technology of net plant capacity 418MW. We normalize the bids and scale the costs accordingly for the six actual combined cycle units for which data are collected. For the role of natural gas price in CC unit variable cost, EIA reports that the average natural gas price in NY is 17% higher than the Henry Hub natural gas spot price. The variable cost is adjusted for this price mark up.

Risk-free benchmark revenue and total cost depend on the bidding behavior of the CC natural gas units. Hourly representative bid curves are generated to capture CC unit's bidding behavior by fitting a bid curve to the six sample unit's bid curves. Variation in the bid curves arise due to daily variation in natural gas price and other seasonal effects. The dynamic representative bid curves are created by first factoring out the role of natural gas price on each unit's bid curve as follows.

$$y_{base_t} = y_t - \frac{N_t}{\nu}, \tag{20}$$

where $y_t$ is the \$/MW bid price and $\nu$ is the average efficiency of a CC unit, taken as 60%. After the natural gas factor is filtered, the bid curves for the selected CC units are grouped by seasons. For each season, a representative bid curve is fitted to the reduced bid curves data for the six CC units. The fitted bid curves are constrained to be continuous and non-decreasing. The seasonal representative bid curves are re-adjusted to account for the daily variation in natural gas spot price. These bid curves are used in Equation 18 for computing the daily revenue and return of the risk-free benchmark.

# 4 Risk-free Tranche Design and Performance Results

We implement the risk-free tranche design and evaluation presented in Section 2 based on some of the assets included in this study. As stated earlier, we have conducted this study based on renewable assets, constituting of wind and solar resources, in New York and Texas geographies. For the sake of focus and brevity, results are presented here based on specific wind and solar resources located in New York state. We will begin by presenting results of *characteristic days* analysis for these assets, followed by results of risk-free tranche definition, pricing and evaluation for some characteristic days of these assets.

## 4.1 Characteristic Day Identification

Days of similar generation and forecast risk profile are identified for each renewable asset using clustering analysis conducted on 11 relevant key daily statistics. The top two rows of Tables 3 and 4 show the 11 summary statistics features used for clustering defined in terms of hourly generation and forecast time series for the day. The centroid coordinates summarized in the two tables describe the nature of each characteristic day, where 6 is the optimal number of clusters chosen based on k-means elbow curves.

Table 3 shows that the solar asset's L0 cluster (labeled in red) has lowest mean generation and L4 cluster (labeled in green) has the second highest mean generation level, each containing 217 days and 146 days, respectively, from among the total number of days in our data. The highest mean generation cluster, L5, also displays higher maximum and minimum forecast error than the L4 cluster, while containing fewer days in the cluster. L4 days have higher forecast error compared to L0 days, implying that when amount of generation is high the accuracy of forecasting shows greater variability, which is seen for other high mean generation clusters, L3 and L5. Among the remaining low generation clusters, namely L1 and L2, coefficient of variation of generation of L2 cluster is significantly lower than that of L0 and L1 clusters, while maximum forecast error in L2 is significantly lower than that in L1 cluster. Therefore, L2 cluster is a more cohesive cluster, even

| Chr Day | Mean Gen | Std of Gen | Hour of max gen | Hour of max error | Hour of min error | Max gen | Max forecast error | Min forecast error | Post-noon /Pre-noon mean Gen | 2pm- -10pm Gen | # of days |
|---|---|---|---|---|---|---|---|---|---|---|---|
| L0 | 1.52 | 2.4 | 11.9 | 7.49 | 11.67 | 7.23 | 1.65 | -5.58 | 1.77 | 5.00 | 217 |
| L1 | 5.96 | 8.45 | 12.37 | 12.05 | 11.62 | 24.39 | 8.99 | -4.61 | 2.08 | 17.08 | 165 |
| L2 | 6.05 | 7.99 | 12.9 | 9.88 | 13.86 | 23.42 | 5.72 | -11.6 | 2.05 | 47.47 | 42 |
| L3 | 12.4 | 16.86 | 12.44 | 11.34 | 13.23 | 46.63 | 17.32 | -9.63 | 2.06 | 15.66 | 61 |
| L4 | 12.73 | 15.68 | 12.62 | 11.77 | 12.69 | 40.85 | 9.47 | -4.21 | 1.84 | 36.87 | 146 |
| L5 | 15.59 | 19.41 | 12.68 | 10.63 | 14.86 | 51.07 | 13.34 | -13.65 | 2.14 | 46.25 | 98 |

Table 3: Centroid coordinates of 6 characteristic days for New York solar resource

if it only has 42 days in it. To demonstrate properties of the risk-free tranche in more productive and less productive type of days, we conduct rest of the analysis for L0 and L4 clusters for this solar asset.

| Chr Day | Mean Gen | Std of Gen | Hour of Min Gen | Hour of Max Gen | Hour of Min Err | Hour of Max Err | Max Err | Min Err | 12am -Noon Gen | Min Gen | Max Gen | # of Days |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| L0 | 7.87 | 6.39 | 9.65 | 11.02 | 11.60 | 10.73 | 13.21 | -9.79 | 4.53 | 0.81 | 21.76 | 419 |
| L1 | 19.34 | 12.82 | 10.31 | 10.83 | 10.82 | 12.11 | 20.09 | -15.97 | -41.60 | 3.78 | 45.46 | 150 |
| L2 | 25.09 | 16.83 | 11.51 | 12.14 | 11.68 | 12.18 | 24.24 | -19.50 | 6.50 | 4.53 | 58.09 | 293 |
| L3 | 46.75 | 21.47 | 12.59 | 11.16 | 11.32 | 12.67 | -5.38 | -78.17 | 3.92 | 15.22 | 81.22 | 63 |
| L4 | 46.88 | 25.01 | 10.34 | 11.75 | 12.07 | 11.03 | 35.24 | -19.70 | 39.82 | 11.55 | 89.80 | 169 |
| L5 | 57.29 | 24.42 | 11.50 | 11.88 | 12.96 | 12.56 | 32.37 | -17.98 | -19.79 | 0.59 | 95.33 | 245 |

Table 4: Centroid coordinates of 6 characteristic days for New York wind resource

Table 4, showing the characteristic days for the New York wind asset, indicates that wind generation has overall high mean generation as well as higher standard deviation of generation, although coefficient of variation in all characteristic days is below 1. Among specific clusters, L0 has the lowest mean generation (labeled red) and L4 & L5 are among the highest mean generation clusters.

L4 & L5 days have similar standard deviation of generation, even though L5 has a significantly higher mean generation level, suggesting L5 cluster with 245 days is a fairly productive cluster of days. As before, increasing mean generation among these clusters corresponds to higher maximum and minimum forecast error, with cluster L3 showing the peculiar property of the maximum forecast error also being negative. This feature and the midnight-noon generation feature offer the two primary distinctions between L3 and L4 days, with all other cluster characteristics being quite comparable. Once again, to focus on comparison of the risk-free tranche among different kind of days, we will present rest of the analysis for L4 and L5 wind resource days.

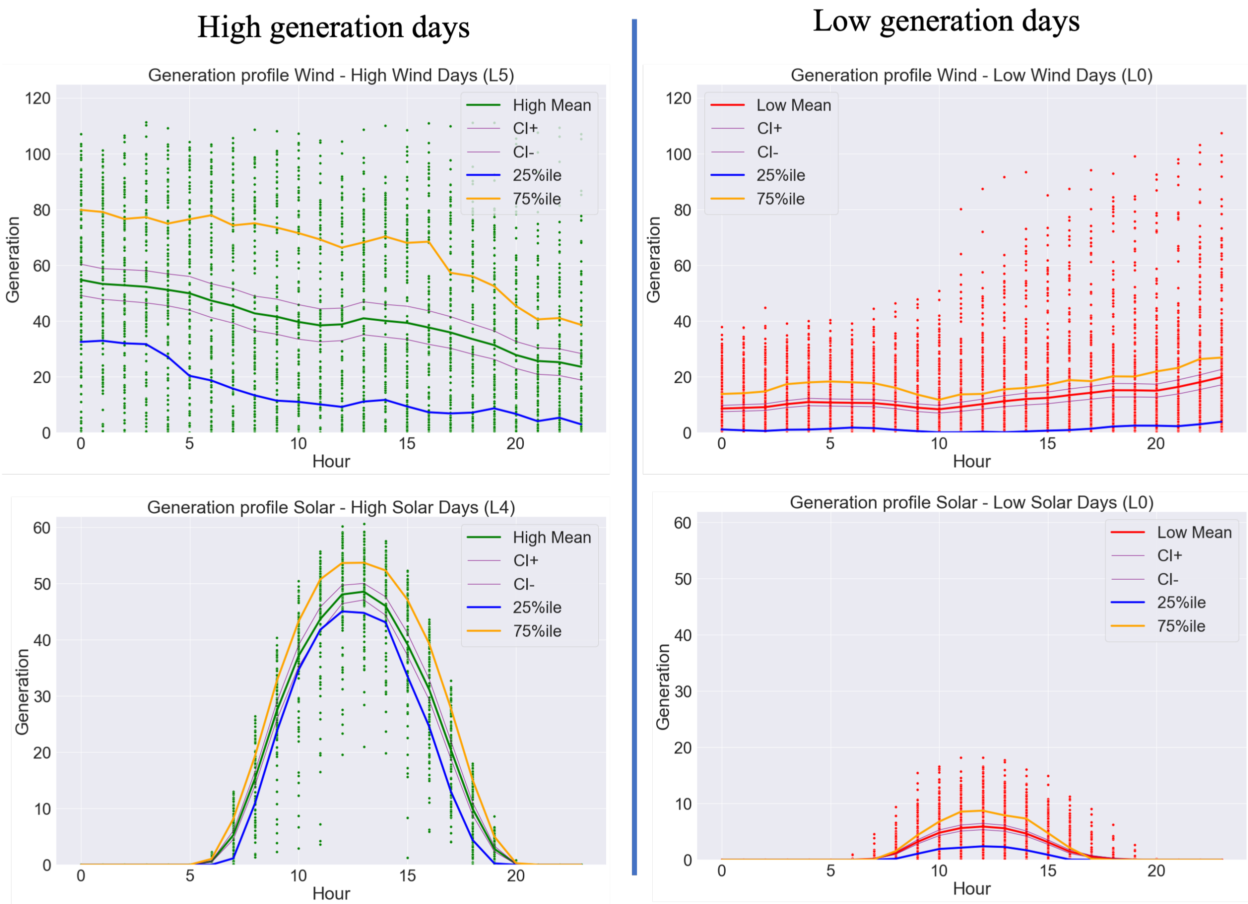


Figure 2: Hourly generation profile of wind and solar units for the high generation and low generation cluster days

Since the risk-free tranche is implemented for each hour of each day, just evaluating the daily characteristics of each characteristic day cluster doesn't suffice. Figure 2 shows the 24-hour generation profile of specific characteristic days, high and low, to highlight how the generation level changes by the hour of the day for the wind (top panel) and solar (bottom panel) asset. These plots show the raw generation levels for each hour for days in that cluster, the hourly mean generation, 95% confidence interval for the mean, and hourly $25^{th}$ & $75^{th}$ percentiles of generation. The plots show that each characteristic day exhibits a unique risk profile, with striking differences between high and low generation characteristic days. Besides the stark difference in the generation level, the generation profile of high wind days shows a decreasing trend in the 24-hour period, whereas low wind days exhibit a steady low level of generation with ever so slight upward trend. The high solar generation cluster shows sharp rise as the sun rises in the morning with a much smaller inter-quartile range through out the day, while the low solar generation cluster rises very gradually, settles at a much lower peak with a relative large inter-quartile range. These properties of the different characteristic days of different renewable generation resources will have a bearing on the definition of hourly risk-free tranche and the corresponding bidding strategy, which will be demonstrated in the next section.

## 4.2 Risk-free Tranche Results

The characteristic days are days of similar statistical characteristics as identified by clustering based on 11 key daily summary statistics for generation and forecast time series. Treating the data points in a characteristic day as independent and identically distributed, we can estimate the percentiles by which risk-free tranche's hourly attachment and detachment points can be estimated. Section 2.1 discussed the selection of percentiles of generation distribution as attachment and detachment to match the reliability of the risk-free benchmark. Table 3 lists the hourly attachment point of the risk-free tranche for 2 characteristic days each for the wind and solar asset at $4^{th}$ percentile of their respective generation distribution. The detachment point is set at $7^{th}$ and $9^{th}$ percentiles, respectively, for the solar and the wind asset. We see that there are many hours of the day for the wind and solar assets when the risk-free tranche cannot be extracted due to low levels of generation. For these definitions of the risk-free tranche, we next compute the bid price point for each percentile from the attachment to the detachment point of the tranche.

### 4.2.1 Computing Risk-free Tranche Bid Curves

For constructing the risk-free tranche bid curves based on their definitions from earlier in this section, we need to have models to estimate the day-ahead and real-time power market prices, as well as identify the minimum entropy risk neutral measure to implement the pricing in Equation 3. We describe these two components of tranche valuation next.

| Asset | Wind Unit | | | |
|---|---|---|---|---|
| MW capacity | 135.5 MW | | | |
| Characteristic day type | High Wind Days (**L5**) | | Medium Wind Days (**L4**) | |
| Hour /Day Type | Attachment Point (4th Percentile) | Detachment Point (9th Percentile) | Attachment Point (4th Percentile) | Detachment Point (9th Percentile) |
| **0** | 3.88 | 12.60 | 5.25 | 13.67 |
| **1** | 2.78 | 9.06 | 7.44 | 14.27 |
| **2** | 2.24 | 6.73 | 8.42 | 14.92 |
| **3** | 0.74 | 6.99 | 6.44 | 16.01 |
| **4** | 0.18 | 4.90 | 2.40 | 14.17 |
| **5** | 0.68 | 5.50 | 4.91 | 10.07 |
| **6** | 0.18 | 3.80 | 5.56 | 10.56 |
| **7** | 0.20 | 1.98 | 4.04 | 7.11 |
| **8** | 0.28 | 3.48 | 3.00 | 7.11 |
| **9** | 0.10 | 3.49 | 1.40 | 4.71 |
| **10** | 0.08 | 2.89 | 0.20 | 3.84 |
| **11** | 0.00 | 1.70 | 0.37 | 3.21 |
| **12** | 0.08 | 5.26 | 0.10 | 3.55 |
| **13** | 0.28 | 4.49 | 0.00 | 3.00 |
| **14** | 0.58 | 5.90 | 0.00 | 1.12 |
| **15** | 0.55 | 7.16 | 0.00 | 1.20 |
| **16** | 1.08 | 5.87 | 0.00 | 0.77 |
| **17** | 0.86 | 3.80 | 0.07 | 0.77 |
| **18** | 0.50 | 3.18 | 0.00 | 0.40 |
| **19** | 0.38 | 2.80 | 0.00 | 0.41 |
| **20** | 0.50 | 3.78 | 0.07 | 0.71 |
| **21** | 0.00 | 2.17 | 0.00 | 0.42 |
| **22** | 0.17 | 1.59 | 0.00 | 0.40 |
| **23** | 0.17 | 1.96 | 0.00 | 1.21 |

| Asset | Solar Unit | | | |
|---|---|---|---|---|
| MW capacity | 68.5 MW | | | |
| Characteristic day type | High Solar Days (**L4**) | | Low Solar Days (**L0**) | |
| Hour /Day Type | Attachment Point (4th Percentile) | Detachment Point (7th Percentile) | Attachment Point (4th Percentile) | Detachment Point (7th Percentile) |
| **0** | 0.00 | 0.00 | 0.00 | 0.00 |
| **1** | 0.00 | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 | 0.00 |
| **4** | 0.00 | 0.00 | 0.00 | 0.00 |
| **5** | 0.00 | 0.00 | 0.00 | 0.00 |
| **6** | 0.00 | 0.00 | 0.00 | 0.00 |
| **7** | 0.12 | 0.42 | 0.00 | 0.00 |
| **8** | 3.71 | 4.19 | 0.03 | 0.04 |
| **9** | 9.68 | 11.31 | 0.25 | 0.43 |
| **10** | 14.04 | 18.12 | 0.46 | 0.67 |
| **11** | 19.65 | 24.63 | 0.59 | 0.74 |
| **12** | 25.98 | 28.03 | 0.60 | 0.91 |
| **13** | 26.58 | 29.71 | 0.55 | 0.78 |
| **14** | 25.80 | 28.24 | 0.43 | 0.61 |
| **15** | 19.43 | 20.70 | 0.15 | 0.31 |
| **16** | 9.25 | 11.18 | 0.00 | 0.00 |
| **17** | 2.14 | 4.70 | 0.00 | 0.00 |
| **18** | 0.01 | 0.37 | 0.00 | 0.00 |
| **19** | 0.00 | 0.00 | 0.00 | 0.00 |
| **20** | 0.00 | 0.00 | 0.00 | 0.00 |
| **21** | 0.00 | 0.00 | 0.00 | 0.00 |
| **22** | 0.00 | 0.00 | 0.00 | 0.00 |
| **23** | 0.00 | 0.00 | 0.00 | 0.00 |

Figure 3: Attachment and detachment points for the risk-free tranche for the wind and solar units corresponding to two different characteristic days each.

Using the load, natural gas price, day-ahead market price and real-time market price data for New York–Zone A from 2013 to 2020, we implement the regression models from Section 2.2.1 after removing extreme outliers. The results of the regression analysis in Table 5 show that 85% to 90% variation in the dependent variables is explained by the independent variables. These results are consistent across different zones of New York and Texas. Using the real-time market price model, we generate multiple stochastic realizations of the real-time market price by sampling from the fitted distribution to the residual errors and adding them to $\hat{R}_{t+1}$.

The optimization formulation in Equation 10 is implemented to compute a minimum entropy risk neutral probability (Q) for the risk-free tranche valuation. Figure 4 shows the physical probabilities, $p_i$, and the risk neutral probabilities, $q_i$, for the $V_t = \frac{R_{t+1}}{D_t}$ ratio computed for New York-Zone A. Under the assumption of stationary distribution of $V_t$, values of 'V' being higher than 1 correspond to higher real-time price (spot price) relative to day-ahead market price (forward price), while 'V' values lower than 1 indicate the reverse. The physical probability puts higher weights at the two tail values of 'V,' while the risk-neutral probability obtained from the solution of the

| New York-Zone A | $D_t$ | $R_{t+1}$ |
|---|---|---|
| $\hat{D}_t$ | | 1.13*** |
| | | (0.01) |
| $L_{t-1}$ | 0.01*** | -0.00*** |
| | (0.00) | (0.00) |
| $N_{t-1}$ | 3.42*** | 0.33*** |
| | (0.04) | (0.00) |
| R-squared | 0.89 | 0.84 |
| R-squared Adj. | 0.89 | 0.84 |
| Observations | 66552 | 62556 |

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 5: Electricity price regression model results for DAM & RTM

optimization problem shifts the probability weights to higher values of 'V.' This shift of probability assigns higher weight on higher spot price outcomes relative to day-ahead or forward price outcomes. Therefore, state prices for these more unfavorable states are higher.


Figure 4: Physical and risk neutral probabilities for power market prices.

Based on the day-ahead and real-time market prices and the estimated risk-neutral probabilities, we implement the pricing framework of Equation 3 for the range of percentile points between the risk-free tranche's attachment and detachment points. We show the bid curves for two time points shown in Table 6, which are peak load and off-peak load hours, for the wind and solar assets for their respective high generation characteristic days. These two specific off-peak and peak load times are chosen to differentiate and compare bid curves by time of day.

| Geography | Resource | Peak Time | Off-Peak Time |
|---|---|---|---|
| NY (Zone A) | Solar | 2PM | 7AM |
| | Wind | 2PM | 12AM |

Table 6: Sample peak and off peak load hours on a high generation characteristic day for which the bid curves are generated.

A renewable asset must bid competitively in the day-ahead market to become a qualified generating resource. The renewable bids, if uniformly set higher than the bids made by the traditional generators, will result in the renewable generator not being able to procure day-ahead power contracts. Competitive bids by the renewable asset are achieved by choosing the parameter, $\eta_{rf}$, which is the discount loading applied to the baseline deterministic pricing kernel. However, increasing risk borne by the renewable generator at higher percentiles in the attachment-detachment points range must be compensated, and $\lambda_{rf}$ parameter serves this cause as the risk aversion parameter measuring the expected rate of reward per unit risk sought for the real-time market price risk.

Each renewable asset must strategically choose these two parameters for the desired risk-return tradeoff, guided by the asset's technical characteristics, such as the characteristic day type, seasonal variation, storage capabilities and anticipated bids from other generators, etc. The parametric choice of $\eta_{rf}$ and $\lambda_{rf}$ for the specific assets being studied are evaluated and set at 0.4 and 1.0, respectively. This parametric choice puts the entire risk-free tranche bid curve at an attractive range in the day-ahead market for all hours of the day. Same parameter levels are used for both the renewable assets for all their characteristic days. Figure 5 shows the bid curves for the wind and solar assets in New York-Zone A for the high generation characteristic days, with bid prices in \$/MW aligning for each bid-point of power level (MW) offered. The bid curve starts from the attachment point of the risk-free tranche and ends at the detachment point, linearly interpolated for all points in the middle and reflective of the incremental risk with increasing bid point.

We observe that the risk-free tranche bid curves are responsive to the risk-profile of different characteristic days and the hour of the day. They have different bid-point (MW) levels for different hours of the day, based on the hourly generation risk. The day-ahead market prices are typically higher for peak load times than the off peak load times. This is reflected in the bid price points of \$/MW level of the renewable asset's risk-free tranche bid curve. These hourly bid curves determine

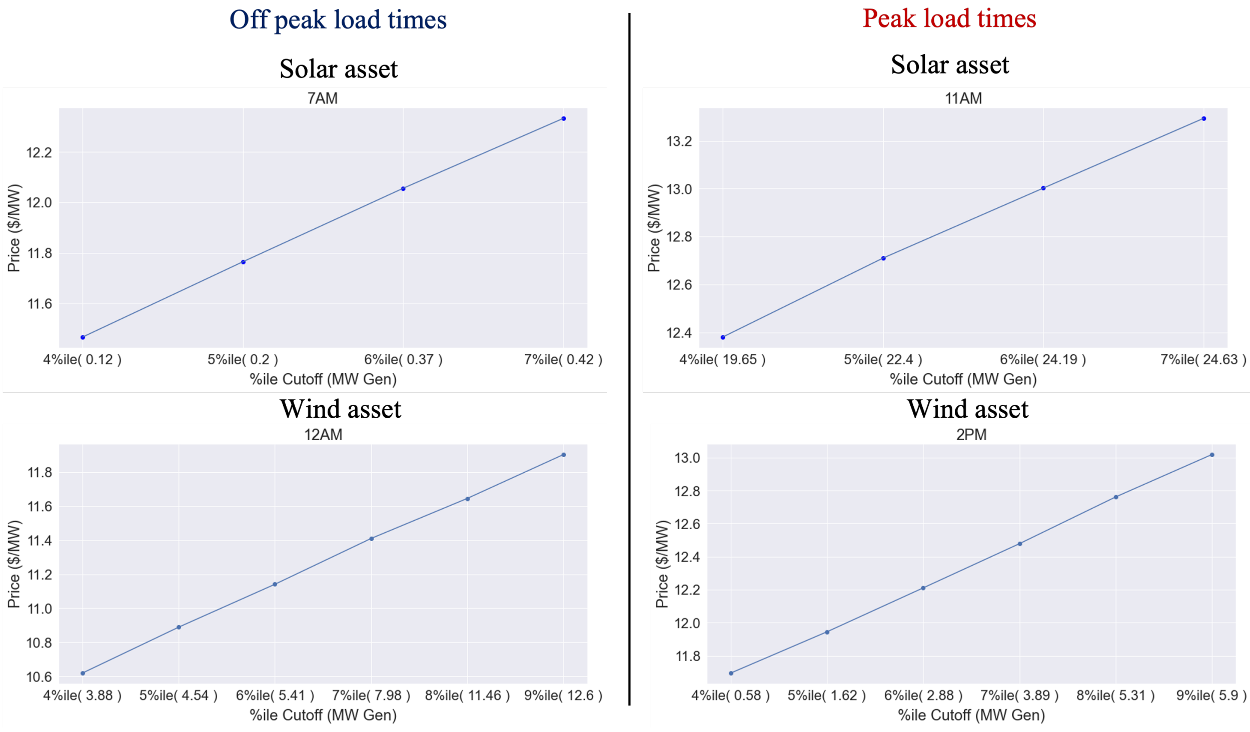


Figure 5: Risk-free bid curves for solar and wind asset in New York-Zone A at peak and off peak load times for high generation days

when a renewable asset's risk-free offer is accepted by the day-ahead market and in doing so, determines the revenue and the return time-series of the renewable asset's risk-free tranche. We conduct the financial performance analysis for the risk-free tranche next.

## 4.3 Risk-free Tranche Performance

To facilitate the financial performance evaluation of the risk-free tranche, we need to implement the risk-free benchmark developed in Section 2.3.1 for New York state. Figure 6 shows the historical reduced bid curves of the six sample CC units selected from different locations in New York state, and the piece-wise linear fitted bid curve for a representative combined cycle natural gas generator in NY. As described in Section 2.3.1, the reduction of the historical bid curves was done to eliminate the role of natural gas prices on the bid curves.

The power sold by the representative CC generator in the day-ahead market is determined by its bid curve posts and the day-ahead market clearing price for the particular hour, as per Equation 18. Using a historic simulation of day-ahead market prices for the time period Jan 2017 to Dec 2020, we generate the representative CC generator's return time series. The fitted bid curve of the representative CC unit from Figure 6 are adjusted daily by the natural gas price, before being

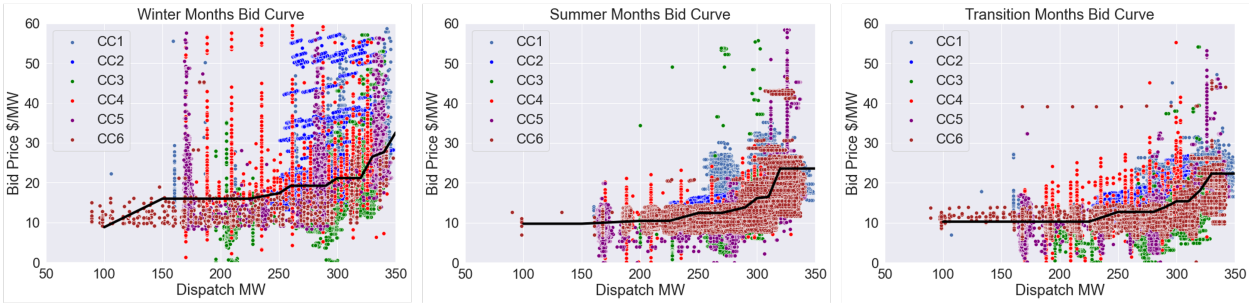


Figure 6: Winter, Summer and Transition months bid curves posted by 6 combined cycle generators in NY and the fitted representative bid curve.

used in Equation 17 to compute the CC unit's daily return. Since four of the six CC units are in Zone J and two are in Zone G, we take a weighted average of the day-ahead and real-time market prices for these two zones for the purpose of this computation. The Sharpe ratio performance metric for the risk-free benchmark is computed based on this return time series. Table 7 summarizes the statistics for the risk-free benchmark daily return time-series and the Sharpe ratio for the risk-free benchmark for the New York power market stands at 0.43.

| | Daily Returns |
|---|---|
| count | 1328.00 |
| mean | 0.17 |
| std | 0.40 |
| min | -0.37 |
| 25% | -0.02 |
| 50% | 0.10 |
| 75% | 0.24 |
| max | 4.93 |

Table 7: Summary statistics for the daily return time series of combined cycle natural gas generator risk-free benchmark.

A similar Sharpe ratio metric is computed for the renewable assets for different characteristic days of the risk-free tranche, and compared against the Sharpe ratio of the risk-free benchmark. We present the performance of the risk-free tranche of solar and wind assets, in terms of both Sharpe ratio as well as analyzing the tail risk of daily returns. For each characteristic day type, Equations 14 and 16 described in Section 2.3 are populated using the quantities computed in this section for the chosen renewable assets. Return time series for different characteristic day types are concatenated to build a more complete return time series to compute the Sharpe ratio of returns. The return distribution is heavily right skewed, hence the Sharpe ratio is estimated under normality assumption to avoid very high positive daily returns biasing the estimates.

**Performance of Solar Asset**: We compute the returns for the two characteristic day types, high generation (L4) and low generation (L0) days, the properties of which were summarized in Table 3. After concatenation there are 363 days, with 146 high solar days and 217 low solar days. Table 8 summarizes the statistics for daily return for the solar asset's risk-free tranche, with the Sharpe ratio of 0.40. The Sharpe ratio of this risk-free tranche is within 5% of the Sharpe ratio of the risk-free benchmark. Since we concatenated the return time series of high and low generation days of the solar asset, inclusion of other medium generation days will produce comparable results. The tail properties of the tranche returns are shown in Table 9 (left tail below $1^{st}$ percentile), Table 10 (specific hours of tail outcomes), and Table 11 (right tail above $99^{th}$ percentile).

The left tail risk in Table 9 arises primarily due to unfavorable spot price outcomes at the times of generation shortfall in the risk-free tranche. For instance, on January 24, 2019 the risk-free tranche contracted 4.48MW, but the actual generation was only 1.46MW, resulting in a shortfall of 3.02MW with the high real-time price risk exposure. To further investigate the left tail risk, some sample hours from January 24, 2019 are shown in Table 10, where for multiple hours the generation shortfall of the risk-free tranche is exposed to high real-time prices resulting in negative cash flows. Additionally, there is only one day when contracting using a risk-free tranche is worse than not contracting, which corresponds to a return less than $-100\%$. On the other hand, high day-ahead prices lead to high returns and the right tail realizations seen in Table 11.

**Performance of Wind Asset**: We compute the returns for highest generation (L5) and medium generation (L4) characteristic days for the wind asset as described in Table 4. The daily returns of the 245 highest wind days are concatenated with the 169 medium wind day returns. We focus on these two characteristic days since the other characteristic day types are not amenable to extracting a risk-free tranche due to low wind productivity. Table 12 summarizes statistics for the wind asset risk-free tranche daily return time series, with a Sharpe ratio of 0.28. While the Sharpe ratio of the wind risk-free tranche is lower than that of the risk-free benchmark, studying the tail characteristics of returns is instructive. Tables 13 and 14 highlight the left tail risk, where former shows return outcomes at below $1^{st}$ percentile and latter shows sample of hours from November 29, 2019 when the worst return is realized. Table 15 shows return outcomes on the right tail above

| | Daily Returns |
|---|---|
| count | 363.00 |
| mean | 0.78 |
| std | 2.07 |
| min | -1.06 |
| 25% | -0.53 |
| 50% | -0.25 |
| 75% | 1.63 |
| max | 13.23 |

Table 8: Summary statistics of daily return for the solar asset risk-free tranche.

| Date | DAM | RTM | Contracted(MW) | Gen(MW) | Shortfall(MW) | Cashflow($) | Returns |
|---|---|---|---|---|---|---|---|
| 2019-01-24 | 91.15 | 1057.73 | 4.48 | 1.46 | 3.02 | -15.58 | -1.06 |
| 2018-02-09 | 769.05 | 747.39 | 4.48 | 1.03 | 3.46 | 9.03 | -0.96 |
| 2019-11-11 | 287.27 | 624.38 | 1.77 | 4.60 | 0.10 | 20.19 | -0.92 |
| 2019-11-07 | 318.92 | 986.28 | 2.00 | 26.16 | 0.00 | 26.36 | -0.89 |

Table 9: Left tail of the return distribution for the solar risk-free tranche in NY-Zone A

$99^{th}$ percentile.

Left tail risk for the wind asset also arises due to spot price exposure at times of generation shortfall. As seen in Table 13, the total power contracted on November 29, 2019 was 57.5MW, however the actual generation was only 0.4MW. A shortfall of 57.1MW was exposed to real-time market price risk. Table 14 shows several hours on November 29, 2019 when high real-time market prices cause generation shortfall to result in negative cash flows. In the case of a wind asset, there are five days when contracting a risk-free tranche is worse off than not contracting. High day-ahead prices lead to high returns and right tail realizations shown in Table 15. Therefore, the tail risk analysis shows that even though the Sharpe ratio of wind risk-free tranche is lower than that of the risk-free benchmark, there is only minimal tail risk and risk-free contracting is better than not contracting on 98.8% of the days.

| Timestamp | DAM | RTM | Contracted(MW) | Gen(MW) | Shortfall(MW) | Cashflow($) |
|---|---|---|---|---|---|---|
| 2019-01-24 08:00:00 | 48.22 | 60.78 | 0.04 | 0.00 | 0.04 | -0.30 |
| 2019-01-24 09:00:00 | 37.30 | 69.66 | 0.43 | 0.05 | 0.38 | -10.65 |
| 2019-01-24 10:00:00 | 37.11 | 94.88 | 0.67 | 0.21 | 0.45 | -18.31 |
| 2019-01-24 11:00:00 | 36.98 | 45.53 | 0.74 | 0.23 | 0.51 | 4.23 |
| 2019-01-24 12:00:00 | 32.16 | 41.82 | 0.91 | 0.32 | 0.59 | 4.52 |

Table 10: Sample hours of the day with highest negative return for the Solar asset in NY-Zone A

| Date | DAM | RTM | Contracted(MW) | Gen(MW) | Shortfall(MW) | Cashflow($) | Returns |
|---|---|---|---|---|---|---|---|
| 2018-06-01 | 2120.41 | 964.32 | 181.62 | 286.88 | 0.00 | 26751.69 | 12.21 |
| 2018-07-04 | 2017.59 | 1171.51 | 181.62 | 317.62 | 0.00 | 26798.40 | 12.24 |
| 2018-06-02 | 2105.53 | 1927.90 | 181.62 | 246.62 | 0.01 | 28434.80 | 13.04 |
| 2018-07-03 | 2162.59 | 1196.53 | 181.62 | 365.69 | 0.00 | 28801.44 | 13.23 |

Table 11: Right tail of the return distribution for the solar risk-free tranche in NY-Zone A

# 5 Conclusion and Future Work

Renewable energy investment is being aggressively sought globally to meet the future energy demand, which presses the challenge of managing the inherent stochasticity of renewable energy resources, such as wind and solar generation. In this paper, we applied financial engineering asset securitization principles to carve out risk-free generation capability from wind and solar energy resources. The risk-free tranche definition of securitization utilized the generation risk profile of the renewable assets, which dynamically adapts the attachment and detachment points of the risk-free tranche as per the generation risk profile. A minimum entropy risk-neutral pricing framework was developed to determine the market-based bid curves for the risk-free tranche. And finally, we evaluated the risk-free tranche performance against a carefully defined risk-free benchmark for the day-ahead power markets.

Our implementation of the proposed risk-free offering framework based on wind and solar assets showed that the risk-free tranche matches the risk-free benchmark in reliability, and is comparable in financial performance to the risk-free benchmark. While we have implemented the framework in all geographies of New York and Texas, the results shown in this paper focus on New York-Zone A. The solar risk-free tranche performs better than the wind risk-free tranche in this zone in terms of

| | Daily Returns |
|---|---|
| count | 414.00 |
| mean | 0.30 |
| std | 1.06 |
| min | -1.17 |
| 25% | -0.31 |
| 50% | 0.14 |
| 75% | 0.68 |
| max | 8.53 |

Table 12: Summary statistics of daily return for the wind asset risk-free tranche.

| Date | DAM | RTM | Contracted(MW) | Gen(MW) | Shortfall(MW) | Cashflow($) | Returns |
|---|---|---|---|---|---|---|---|
| 2019-11-29 | 327.92 | 497.31 | 57.56 | 28.9 | 57.16 | -349.19 | -1.17 |
| 2019-12-16 | 339.68 | 572.61 | 59.53 | 14.5 | 54.76 | -289.27 | -1.14 |
| 2018-12-30 | 357.84 | 448.01 | 59.58 | 0.0 | 59.58 | -115.47 | -1.07 |
| 2020-08-28 | 488.01 | 753.15 | 111.08 | 184.7 | 37.92 | -136.46 | -1.07 |

Table 13: Left tail of the return distribution for the wind risk-free tranche in NY-Zone A

Sharpe ratio, even though in both cases of risk-free tranche there is minimal tail risk. Barring a very limited few number of days, contracting a risk-free tranche in the day-ahead market is better than not contracting. A comparably and reliably performing risk-free tranche developed in this study can provide the necessary assurance to power grid system operators to incorporate the renewable assets based risk-free tranche in the typical day-ahead unit commitment and economic dispatch decisions.

As per U.S. Energy Information Administration (EIA), approximately 95% of the electricity demand is settled in the day-ahead power markets. Therefore, enabling renewable resources to competitively participate in the day-ahead market and enabled to manage the inherent generation risk of renewable assets will help diversify the energy mix and reduce dependence on conventional fossil fuels. Renewable generators being able to competitively participate in day-ahead market using a market-based, risk-responsive bidding strategies will enhance their profitability and achieve a desired risk-return tradeoff. A deteriorating climate necessitates empowering renewable generators

| Timestamp | DAM | RTM | Contracted(MW) | Gen(MW) | Shortfall(MW) | Cashflow($) |
|---|---|---|---|---|---|---|
| 2019-11-29 08:00:00 | 15.67 | 24.09 | 3.48 | 0.2 | 3.28 | -24.48 |
| 2019-11-29 09:00:00 | 16.66 | 29.53 | 3.49 | 0.0 | 3.49 | -44.91 |
| 2019-11-29 10:00:00 | 16.94 | 27.02 | 2.89 | 0.1 | 2.79 | -26.44 |
| 2019-11-29 11:00:00 | 16.98 | 22.51 | 1.70 | 0.1 | 1.60 | -7.15 |
| 2019-11-29 12:00:00 | 17.01 | 20.15 | 5.26 | 0.0 | 5.26 | -16.52 |

Table 14: Sample hours of the day with highest negative return for the Wind asset in NY-Zone A

| Date | DAM | RTM | Contracted(MW) | Gen(MW) | Shortfall(MW) | Cashflow($) | Returns |
|---|---|---|---|---|---|---|---|
| 2018-01-08 | 2804.14 | 921.55 | 111.08 | 2068.0 | 0.00 | 13014.92 | 5.50 |
| 2019-01-23 | 1881.28 | 565.54 | 133.64 | 1926.5 | 0.00 | 10249.14 | 5.82 |
| 2018-01-06 | 4236.42 | 5388.22 | 111.08 | 1357.8 | 5.46 | 16577.41 | 7.29 |
| 2018-01-03 | 2453.46 | 3336.51 | 133.64 | 1244.9 | 0.00 | 14320.67 | 8.53 |

Table 15: Right tail of the return distribution for the wind risk-free tranche in NY-Zone A

with appropriate risk mitigation methodologies to tackle generation risk and become profitable. This ability to manage risk and improve profitability will increase investment in green energy and help reduce carbon emissions, which can yield massive benefits of alleviating climate change.

There are many ways the current study can be enhanced, such as using more data for generation and forecast error, as well as their evolving trends for the future with changes in technology or climate patterns, and a resulting impact on the definition and prediction of characteristic days. On some characteristic days, we saw no prospect of extracting a reliable risk-free tranche. On such days, alternate risk management strategies must be developed, such as those motivated by defining riskier than risk-free tranches, which must also be appropriately priced and bid in the day-ahead market. When a risk-free tranche is unable to meet the obligation due to less than expected actual generation, we assumed that the renewable generator will acquire the shortfall from the real-time market to make up for the shortfall. While this is reasonable for the risk-free tranche, where only a small fraction of the renewable generator's generation capacity is bid, for higher and riskier bids, this assumption may have to be revisited.

There is a very high level of interest and investment in improving energy storage technologies, which can be used to enhance the risk-responsive bidding strategies for renewable generators developed in this paper. Storage capability can help smooth the generation risk and make higher cut-offs for the tranches' attachment and detachment point possible, thus further improving competitiveness and profitability of renewable generators. A key advancement needed in tandem with the risk management innovation developed in this paper is the capability of power markets to seamlessly incorporate the bids from renewable assets with appropriate upgrades in their unit commitment and economic dispatch formulations.

## References


Alafita, T. and Pearce, J. (2014). Securitization of residential solar photovoltaic assets: costs, risks and uncertainty. *Energy Policy*, 67:488–498.

Avellaneda, M. (1998). Minimum-relative-entropy calibration of asset-pricing models. *International Journal of theoretical and applied finance*, 1(04):447–472.

Bessembinder, H. and Lemmon, M. L. (2002). Equilibrium pricing and optimal hedging in electricity forward markets. *the Journal of Finance*, 57(3):1347–1382.

Bhattacharya, S., Gupta, A., Kar, K., and Owusu, A. (2020). Risk management of renewable power producers from co-dependencies in cash flows. *European Journal of operational research*, 283(3):1081–1093.

Bierbrauer, M., Menn, C., Rachev, S. T., and Trück, S. (2007). Spot and derivative pricing in the eex power market. *Journal of banking & finance*, 31(11):3462–3485.

Bird, L., Lew, D., Milligan, M., Carlini, E. M., Estanqueiro, A., Flynn, D., Gomez-Lazaro, E., Holttinen, H., Menemenlis, N., Orths, A., et al. (2016). Wind and solar energy curtailment: A review of international experience. *Renewable and Sustainable Energy Reviews*, 65:577–586.

Brockett, P. L., Wang, M., and Yang, C. (2005). Weather derivatives and weather risk management. *Risk Management and Insurance Review*, 8(1):127–140.

Cartea, Á. and Villaplana, P. (2008). Spot price modeling and the valuation of electricity forward contracts: The role of demand and capacity. *Journal of Banking & Finance*, 32(12):2502–2519.

Center, B. P. (2020). Annual energy outlook 2020. Technical report, Energy Information Administration. https://www.eia.gov/outlooks/aeo/pdf/AEO2020%20Full%20Report.pdf.

Coulon, M., Powell, W. B., and Sircar, R. (2013). A model for hedging load and price risk in the texas electricity market. *Energy Economics*, 40:976–988.

Das, S. and Basu, M. (2020). Day-ahead optimal bidding strategy of microgrid with demand response program considering uncertainties and outages of renewable energy resources. *Energy*, 190:116441.

Deloitte (2022). 2022 renewable energy industry outlook. Technical report, Deloitte. https://www2.deloitte.com/us/en/pages/energy-and-resources/articles/renewable-energy-outlook.html.

Deng, S.-J. and Oren, S. S. (2006). Electricity derivatives and risk management. *Energy*, 31(6-7):940–953.

Dewey, R. and Nelson, E. (2020). Achieving a reliable zero-emissions grid by 2040. Technical report, NYISO. https://www.nyiso.com/documents/20142/17122673/Guide-for-the-Climate-Action-Council.pdf/38f2e3c1-7112-61e9-0381-d2f0e2763a72.

Dhaene, J., Stassen, B., Devolder, P., and Vellekoop, M. (2015). The minimal entropy martingale measure in a market of traded financial and actuarial risks. *Journal of Computational and Applied Mathematics*, 282:111–133.

Doege, J., Fehr, M., Hinz, J., Lüthi, H.-J., and Wilhelm, M. (2009). Risk management in power markets: the hedging value of production flexibility. *European Journal of Operational Research*, 199(3):936–943.

EIA (2020). Capital cost and performance characteristic estimates for utility scale electric power generating technologies. Technical report, U.S. Energy Information Administration. https://www.eia.gov/analysis/studies/powerplants/capitalcost/.

EIA (2021). Renewables became the second-most prevalent U.S. electricity source in 2020. Technical report, U.S. Energy Information Administration. https://www.eia.gov/todayinenergy/detail.php?id=48896.

EOEEA (2020). MA decarbonization roadmap. Technical report, Massachusetts Executive Office of Energy and Environmental Affairs. https://www.mass.gov/doc/ma-decarbonization-roadmap-lower-resolution/download.

Eydeland, A. and Wolyniec, K. (2002). *Energy and power risk management: New developments in modeling, pricing, and hedging*, volume 97. John Wiley & Sons.

Falbo, P., Felletti, D., and Stefani, S. (2010). Integrated risk management for an electricity producer. *European Journal of Operational Research*, 207(3):1620–1627.

Ferruzzi, G., Cervone, G., Delle Monache, L., Graditi, G., and Jacobone, F. (2016). Optimal bidding in a day-ahead energy market for micro grid under uncertainty in renewable energy production. *Energy*, 106:194–202.

Frittelli, M. (2000). The minimal entropy martingale measure and the valuation problem in incomplete markets. *Mathematical finance*, 10(1):39–52.

Gabig, N., Cohen, B., and Kapoor, M. (2015). Solar abs: understanding market potential. *The Journal of Structured Finance*, 21(1):105–110.

Girish, G. and Vijayalakshmi, S. (2013). Determinants of electricity price in competitive power market. *International Journal of Business and Management*, 8(21):70.

Gupta, A. (2014). *Risk management and simulation.* Taylor & Francis, Boca Raton.

Hain, M., Schermeyer, H., Uhrig-Homburg, M., and Fichtner, W. (2018). Managing renewable energy production risk. *Journal of banking & finance*, 97:1–19.

Hörnlein, L. (2019). The value of gas-fired power plants in markets with high shares of renewable energy: a real options application. *Energy Economics*, 81:1078–1098.

Hyde, D. and Komor, P. (2014). Distributed PV and securitization: made for each other? *The Electricity Journal*, 27(5):63–70.

IRENA (2017). Adapting market design to high shares of variable renewable energy. Technical report, International Renewable Energy Agency Abu Dhabi. https://www.irena.org/publications/2017/May/Adapting-Market-Design-to-High-Shares-of-Variable-Renewable-Energy.

Jiang, J. N. and Chen, H. (2005). Integrating the power industry into the larger economy via electricity-backed asset securitization. *The Electricity Journal*, 18(6):46–54.

Kehlhofer, R., Rukes, B., Hannemann, F., and Stirnimann, F. (2009). *Combined-cycle gas and steam turbine power plants*. PennWell, Inc., Tulsa, OK (USA). 3rd edition.

Kiesel, R. and Paraschiv, F. (2017). Econometric analysis of 15-minute intraday electricity prices. *Energy Economics*, 64:77–90.

Krupa, J. and Harvey, L. D. (2017). Renewable electricity finance in the United States: a state-of-the-art review. *Energy*, 135:913–929.

Liang, X. (2016). Emerging power quality challenges due to integration of renewable energy sources. *IEEE Transactions on Industry Applications*, 53(2):855–866.

Liu, W., Wang, J., Xie, J., and Song, C. (2007). Electricity securitization in China. *Energy*, 32(10):1886–1895.

Lowder, T. and Mendelsohn, M. (2013). Potential of securitization in solar pv finance. Technical report, National Renewable Energy Lab.(NREL), Golden, CO (United States). https://www.nrel.gov/docs/fy14osti/60230.pdf.

MacQueen, J. (1967). Classification and analysis of multivariate observations. In *5th Berkeley Symp. Math. Statist. Probability*, pages 281–297.

Mosquera-López, S. and Nursimulu, A. (2019). Drivers of electricity price dynamics: comparative analysis of spot and futures markets. *Energy Policy*, 126:76–87.

Müller, A. and Grandi, M. (2000). Weather derivatives: a risk management tool for weather-sensitive industries. *The Geneva Papers on Risk and Insurance. Issues and Practice*, 25(2):273–287.

Nikpour, A., Nateghi, A., Shafie-khah, M., and Catalão, J. P. (2021). Day-ahead optimal bidding of microgrids considering uncertainties of price and renewable energy resources. *Energy*, 227:120476.

Orlov, A., Sillmann, J., and Vigo, I. (2020). Better seasonal forecasts for the renewable energy industry. *Nature Energy*, 5(2):108–110.

Pérez-González, F. and Yun, H. (2013). Risk management and firm value: Evidence from weather derivatives. *The Journal of Finance*, 68(5):2143–2176.

Pirrong, C. and Jermakyan, M. (2008). The price of power: The valuation of power and weather derivatives. *Journal of Banking & Finance*, 32(12):2520–2529.

Prokhorov, O. and Dreisbach, D. (2022). The impact of renewables on the incidents of negative prices in the energy spot markets. *Energy Policy*, 167:113073.

Prol, J. L., Steininger, K. W., and Zilberman, D. (2020). The cannibalization effect of wind and solar in the california wholesale electricity market. *Energy Economics*, 85:104552.

Roulston, M. S., Kaplan, D. T., Hardenberg, J., and Smith, L. A. (2003). Using medium-range weather forcasts to improve the value of wind energy production. *Renewable Energy*, 28(4):585–602.

Shahidehpour, M., Fu, Y., and Wiedman, T. (2005). Impact of natural gas infrastructure on electric power systems. *Proceedings of the IEEE*, 93(5):1042–1056.

Ssebugenyi, C. S., Mwaniki, I. J., and Konlack, V. S. (2013). On the minimal entropy martingale measure and multinomial lattices with cumulants. *Applied Mathematical Finance*, 20(4):359–379.

Vehviläinen, I. and Keppo, J. (2003). Managing electricity market price risk. *European Journal of Operational Research*, 145(1):136–147.

Wan, C., Zhao, J., Song, Y., Xu, Z., Lin, J., and Hu, Z. (2015). Photovoltaic and solar power forecasting for smart grid energy management. *CSEE Journal of Power and Energy Systems*, 1(4):38–46.

Wang, J., Zhong, H., Tang, W., Rajagopal, R., Xia, Q., Kang, C., and Wang, Y. (2017). Optimal bidding strategy for microgrids in joint energy and ancillary service markets considering flexible ramping products. *Applied Energy*, 205:294–303.

Zarnikau, J., Tsai, C., and Woo, C. (2020). Determinants of the wholesale prices of energy and ancillary services in the U.S. Midcontinent electricity market. *Energy*, 195:117051.

Zarnikau, J., Woo, C., Zhu, S., and Tsai, C. (2019). Market price behavior of wholesale electricity products: Texas. *Energy Policy*, 125:418–428.