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Authors(s)	Cuffe, Paul, Shamsi, Mahdieh
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Using Binary Prediction Markets as Hedging Instruments: Strategies for Renewable Generators

Mahdieh Shamsi, *Student Member, IEEE* and Paul Cuffe, *Member, IEEE*

***Abstract*—Renewable energy sources face volumetric risk in their revenue streams, in any electricity sale structure, due to changeability associated with weather conditions. Weather/power derivatives are often employed to hedge against such financial risks. This letter proposes that a binary prediction market, if is adequately liquid, has the potential to resemble the function of such derivatives to improve the financial profile of renewable sources. The size and the price of shares (contracts) to be purchased by the renewable generator are determined analytically in the methodology of this paper. To this end, two different approaches have been considered: the *indifference* utility condition and the *maximisation of utility* function to reflect different risk preferences of investors.**

I. Introduction

RENEWABLE energy producers face cashflow volatility due to variations in weather patterns. Futures markets have a long history of application in various industries (e.g. agriculture products [1]) to hedge against such uncertainties in revenue streams, yet these are not fully exploited for renewable generators. Power futures markets can be used to hedge against volumetric risk [2] or price uncertainty [3] for power plants. In the case of weather-based renewable sources, specifically, weather derivatives have been discussed in the literature as a viable solution to this problem, either in standard exchange-traded products [2] or bilaterally over the counter [4]. In [5], an irradiance-indexed call option is considered in the energy cost management model of a copper mine with PV installation to cover the risk of cloudy days. To hedge the long-term volumetric risks of solar generators, in [4], a temperature-based swap mechanism is developed via smart contracts programmed on a blockchain platform. In [6], minimum variance hedging of a solar plant through an irradiance-based derivative has been developed against imbalance costs in the electricity market. For the case of Wind Power Producers (WPP), as stated in [7], recently introduced wind power derivatives outperform electricity derivatives, due to the correlation between renewable generation and the electricity price as the underlying index. However, the payoffs of the currently available wind power derivatives only depend on the market-wide wind generation [8]. *Prediction markets* [9] are futures markets where participants trade contracts associated with the outcome of specific future events. While such markets have existed for many years in centralised forms, blockchain technology enables implementing them through a decentralised arrangement [10]. In comparison to the aforementioned power derivatives, prediction market payoffs are more flexible, as they can be defined directly by the local generation. Moreover, wind power derivatives are only available in a few countries while blockchain-hosted prediction markets [11] make them accessible to participants from all locations.

The general idea of using prediction markets for renewables' forecasting and hedging has been proposed in [10]. In [12], authors have employed scalar prediction markets as a hedging tool against imbalance costs in the day-ahead electricity market. In this letter, we propose using a simple *binary* prediction market as a weather derivative to reduce the revenue uncertainty of renewable generators.

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M.Shamsi and P. Cuffe (paul.cuffe@ucd.ie) are with the School of Electrical and Electronic Engineering, University College Dublin.

II. Methodology

A. Binary Prediction Market

Consider a binary prediction market which is asking whether *the wind speed for a particular time period at a nominated WPP site is less than a certain threshold*. In such market two *shares (contracts)* are offered, corresponding to possible answers to this question (YES/NO). Participants buy shares and when the actual correct answer is known will be paid accordingly: one unit of currency per correct share (e.g $1) and otherwise receiving nothing. Note that in our methodology we assume that this prediction market is liquid and a large number of participants exist and actively trade shares. Similar to a derivative exchange, in this context these traders resemble the role of *speculators* and the WPP is a *hedger* who takes an offsetting position in the market. To determine a suitable trading strategy for the WPP in this binary prediction market, the following sections apply two distinct methods to analytically derive the number of shares, available at particular price levels in the market's order book, that should be purchased by this WPP to balance their expected revenue from the physical electricity and prediction markets.

1) Indifference Pricing Strategy: In this section, the trading decisions of the WPP in the prediction market is modelled by adopting utility theory [13] which has previously been applied in power systems literature ([14] and [15]) to model various investment problems. To this end, first we consider an investor participating in a general binary prediction market with $U(w)$ as their utility function, where w represent an amount of wealth. The indifference pricing strategy for such an investor can be achieved by solving (1), which requires that the expected value of the utility remains unchanged [13]:

$$pU(w_0 + n(1-m)) + (1-p)U(w_0 - nm) = U(w_0) \qquad (1)$$

where p is the probability of the outcome of the event in which market resolves YES and n is the number of shares to be purchased, m is the price of shares, w_0 is an assumed initial wealth. For a risk-neutral participant, $U(w) = w$ and therefore equation (1) results in $m = p$ which means that indifference pricing for a risk-neutral trader is independent of the number of shares purchased and is always equal to the expected value of the shares payoff.

However, for a risk-averse participant with a concave utility function (modelled exponentially as in [12]) with the form of $U(w) = -\exp(-bw)$, the indifference pricing by solving (1) results in:

$$m = -\log\left(p\exp(-bn) + 1 - p\right)/(bn) \tag{2}$$

which is a non-linear decreasing function of the number of shares. In (2) b is the risk aversion degree of the investor and the rest of the variables and parameters retain their definitions from (1).

Now we assume that the risk-averse participant is a WPP whose electricity production revenue depends on the wind speed. We consider a prediction market which asks whether the wind speed will be *less* than a certain threshold denoted by v_e. This threshold is the WPP's belief about the expected wind speed for the time period over which they aim to hedge their revenue. Indifference pricing for this WPP by solving (1) results in (3).

If this WPP wants to pursue an indifference pricing strategy, they can use (3) to determine the number of shares denoted by n, at various price points denoted by m, that they ought to purchase as expressed by:

$$m = \frac{1}{bn}\log\frac{p\exp(-bc) + (1-p)\exp(-bg)}{p\exp(-bn-bc) + (1-p)\exp(-bg)} \tag{3}$$

The WPP generation uncertainty is modelled by the Probability Distribution Function (PDF) of the wind speed and therefore p in (3) comes from the Cumulative Density Function (CDF) of the wind speed i.e. $F_V(v_e)$ where F_V is the CDF of wind speed which corresponds to the probability of the wind speed being less than a certain threshold (v_e), being asked in the binary prediction market. In (3), c can be computed by (4) and represents the WPP's belief about the expected revenue from the physical electricity market across all the wind speed scenarios in which the prediction market resolves YES i.e. the wind speed scenarios lower than the considered threshold (v_e). The expected revenue across all the wind speed scenarios above that threshold (v_e) is denoted by g and is computed by (5).

$$c = \int_0^{\omega(v_e)} \lambda\omega f_\Omega(\omega)d\omega \tag{4}$$

$$g = \int_{\omega(v_e)}^{\omega_{max}} \lambda\omega f_\Omega(\omega)d\omega \tag{5}$$

where λ is the electricity price, ω is the WPP power generation and $f_\Omega(\omega)$ represents the PDF of ω. The proposed method only provides hedging against the uncertainty of renewable generation (ω) due to weather changeability and is not aimed at hedging electricity price volatility (reflected in λ), for instance due to demand uncertainty in competitive electricity markets structures.

The expected revenue of the WPP depends on the electricity sale structure which is independent of the proposed prediction

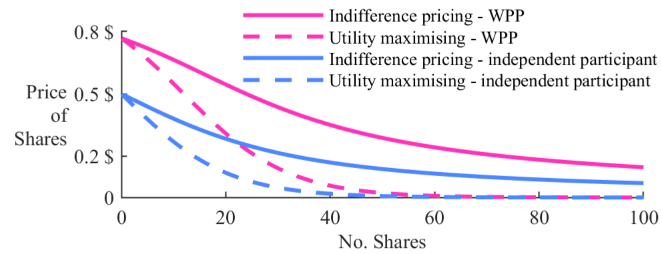

Fig. 1. Comparing the indifference and utility maximising pricing of shares in a prediction market for the WPP and an independent risk-averse participant.

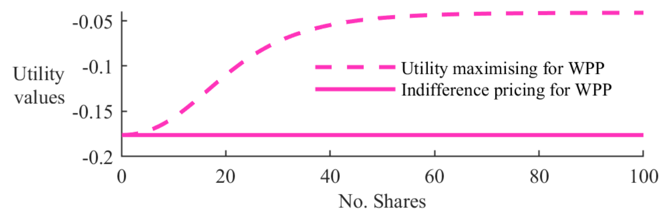

Fig. 2. Comparing utility value of the WPP under two trading strategies in the prediction market.

market. Here, the binary prediction market can be seen as *a pure financial venue* resembling *a weather derivatives exchange* and the limits and constraints of the two markets do not affect each other. Therefore, our method is not confined to any specific electricity sale mechanisms, as it could accommodate a PPA bilaterally between a renewable generator and a electricity consumer/trader or a day-ahead electricity market which is run by a system operator in which the renewable generator participates as a seller.

2) Utility Maximising Strategy: Another approach to determine the trading volume in a binary prediction market with the aim of hedging is to maximise the expected value of the WPP's utility function. The expected utility value for an independent risk-averse participant can be expressed as [13]:

$$U(n,m) = p\exp(-b(n(1-m))) + (1-p)\exp(-b(-nm))) \tag{6}$$

which is a concave function. Differentiating (6) with respect to n and solving $\frac{\partial U}{\partial n} = 0$ gives the price as a function of n as below:

$$m = p/((1-p)\exp(bn) + p) \tag{7}$$

Similarly, for a WPP the expected value of the utility can be expressed as:

$$U(n,m) = p\exp(-b(n(1-m)+c)) + (1-p)\exp(-b(g-nm))) \tag{8}$$

which is a function of the number of shares and the price of shares. Solving $\frac{\partial U}{\partial n} = 0$ gives the price as a function of n as below:

$$m = p/((1-p)\exp(b(n-g+c)) + p) \tag{9}$$

III. Results

To illustrate how the proposed methodology works, we consider a WPP with a 1.5 MW wind turbine, located in a site where the wind speed follows a Weibull distribution with a scaling and a shaping parameter of 8 and 10, respectively, and an expected value of 7.6 m/s. The rated, cut-in and cut-off speed values of wind turbine are 10 m/s, 4 m/s and 30 m/s, respectively. This WPP sells its electricity production via a PPA structure which pays 60 $/Mwh for the energy delivered. Therefore the WPP enjoys electricity price stability but is still exposed to volume risk due to wind speed uncertainty: a binary prediction market is proposed to hedge against this by asking this question for a nominated time period: *Will the wind speed at this site be less than the median (7.7 m/s)* ? From the CDF of the wind speed, we get $F_V(v_e = 7.7) = p = 0.5$, which would be the maximum price offered by a risk neutral participant in this prediction market. Now, we assume that this WPP has a risk aversion degree of $b = 0.1$. With these assumptions, from (4) we get $c = 13$ \$, and from (5) we get $g = 25$ \$.

According to (2), (3), (7), and (9), the maximum price that can be offered by risk-averse participants, to purchase the specific number of shares based on the indifference pricing (Section II-A1) and the utility maximising (Section II-A2) approaches are shown in Fig. 1. As this figure presents, both approaches result in higher prices that can be offered by a *hedger*, here assumed WPP, in comparison to standalone participants. These findings justify the viability of the proposed idea since it implies that this hedger would be willing to pay higher prices and would benefit the speculators which creates market opportunity. Moreover, it can be inferred from this figure that the indifference pricing is always higher than maximising utility pricing for both an independent participant as well as the WPP.

In Fig. 2, the total utility values captured for the WPP by purchasing the shares according to the number and prices specified by the two trading strategies (shown respectively in Fig. 1 with magenta color) are depicted. Note that the utility value in the indifference pricing strategy is equal to the case of trading only the electricity production and is constant. As shown in this figure, trading according to the utility maximising strategy always results in a higher utility value which proves the fact that the WPP will benefit from hedging through purchasing shares in the binary prediction market.

The level of reduction in revenues due to poor weather conditions which is proportional to c affects the trading volume of the hedging strategy in the prediction market. For a specific amount of g, which represents the revenue from which the cash flows predictions derive, the lower c goes, the higher the volume of shares that should be purchased to hedge against the associated financial loss.

If the WPP purchases 10 YES shares ($n = 10$) with a price of $m = 0.55$ \$ per share, as the price in the utility maximising strategy, according to (9), the CDF of their revenue will be as shown in Fig. 3. As depicted by this figure, the revenue will be in a more predictable range by reducing the variance and the downside risk at the cost of reducing the maximum possible revenue. The effect of buying various number and price of shares that might be available in the order book of the binary prediction market are investigated in Fig. 4 and Fig. 5, respectively: an increase in the number of shares alters the shape of the revenue distribution, and the higher the number

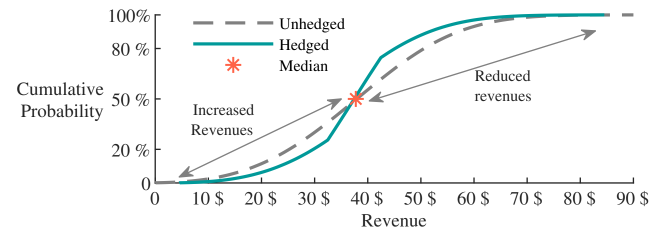

Fig. 3. Comparing the revenue of the WPP in the case of selling electricity only (unhedged case) against hedging through binary prediction market with 10 shares at a price of 0.55 $ per share.

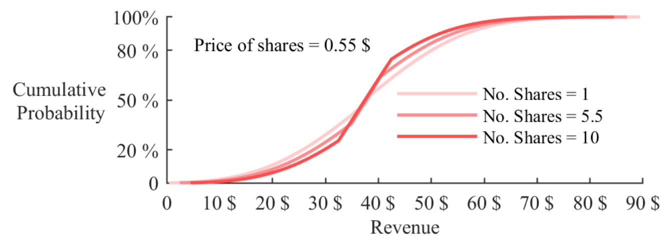

Fig. 4. Effect of increasing the number of shares purchased in a binary prediction market

of shares, the stronger the effect of hedging. An increase in the offered price of available shares shifts the revenue distribution and has a unique impact on all the revenue outcomes. The price of shares based on the utility maximising strategy is computed as $m = 0.55$ \$ per share, according to (9) and also can be tracked on the curve associated with WPP in Fig.1 for $n = 10$. This price stands as the optimal maximum value of price that can be accepted by the WPP and as Fig. 5 shows, any price lower than this, results in higher revenue range with the same variance, which benefits the WPP.

IV. Conclusions

Regardless of the electricity sale scheme and price volatility, renewable sources are always subject to volumetric revenue risks due to changes in weather conditions. Achieving a more stable revenue through hedging instruments is essential for the owners of renewable sources to attract financing parties to the project as well as managing the financial risks during the operational phase. A binary prediction market defined on the predictive weather variables, if it is liquid enough, has the potential to be used as a derivative instrument to reduce the revenue uncertainty of the renewable sources. Compared to available weather exchanges, prediction markets are accessible to a larger group of participants in a wider region and also are more flexible to define the underlying index in terms of location of the site and the forecasting time horizon. Moreover, prediction markets create accurate public predictions, which can be useful for other stakeholders.

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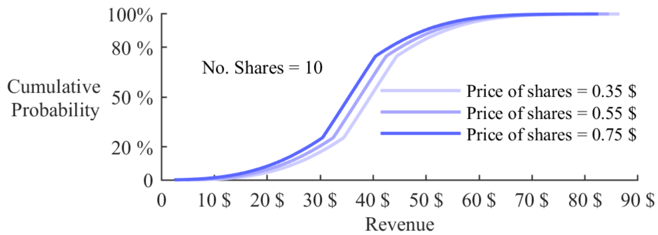

Fig. 5. Effect of increasing the price of shares purchased in a binary prediction market

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