A Prediction Market Trading Strategy to Hedge Financial Risks of Wind Power Producers in Electricity Markets

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***Abstract*—Wind power producers participating in day-ahead electricity markets are compelled to pay imbalance costs if they do not generate the same amount of power as they had bid for. These imbalance costs comprise a significant proportion of their income. To reduce the risk of such financial losses, this paper employs the idea of trading in a separate *prediction market*, as a hedging method. In prediction markets, participants trade shares associated with a certain outcome of an event. We propose that the wind power producers might participate in a prediction market to trade the future value of the wind power and by taking an opposite position in comparison to the electricity market, the imbalance costs will be offset through payouts in the prediction market. Wind power is modelled as a stochastic variable and an optimal trading strategy is developed where the trading volume in the prediction market is analytically derived and formulated by minimising the maximum possible loss and pricing of shares is determined via indifference utility condition. The results suggest that the proposed method limits the loss values and improves the risk measures.**

***Index Terms*—Day-ahead electricity market, hedging, imbalance costs, prediction markets, risk management, wind power producer.**

Nomenclature

λ	imbalance price for overproduction ($\$/\text{MW}h$)
λ_{max}	maximum value of λ ($\$/\text{MW}h$)
λ_{min}	minimum value of λ ($\$/\text{MW}h$)
μ_λ	expected value of λ ($\$/\text{MW}h$)
μ_p	expected value of p (per unit)
μ_q	expected value of q ($\$/\text{MW}h$)
$\rho_{\lambda p}$	correlation coefficient between λ and p
ρ_{qp}	correlation coefficient between q and p
σ_λ	standard deviation of λ ($\$/\text{MW}h$)
σ_p	standard deviation of p (per unit)
σ_q	standard deviation of q ($\$/\text{MW}h$)
b	risk-adversity parameter in the utility function
c^*	per unit value of the bid submitted to the day-ahead electricity market
$F_P(p)$	cumulative distribution function of p
$f_P(p)$	probability distribution function of p
$G(x)$	payoff function of each long share in a prediction market ($\$$)
$G^n(p)$	net payoff of n long shares in the wind power prediction market ($\$$)
$H(x)$	payoff function of each short share in a prediction market ($\$$)
$H^n(p)$	net payoff of n short shares in the wind power prediction market ($\$$)
j	revenue of the wind power producer ($\$$)
k	settlement fees in the prediction market (%)
$L_e(p)$	imbalance cost as a function of p ($\$$)
m	price of shares in a prediction market ($\$$)
$m^*(n)$	indifference utility price as a function of the number of shares, n, in a prediction market ($\$$)
n	number of shares in a prediction market
n^*	number of shares minimising the maximum loss
p	per unit value of the wind power production at the time of delivery
P_{max}	maximum of wind power production (MWh)
q	imbalance price for underproduction ($\$/\text{MW}h$)
q_{max}	maximum value of q ($\$/\text{MW}h$)
q_{min}	minimum value of q ($\$/\text{MW}h$)
r	day-ahead electricity market clearing price ($\$/\text{MW}h$)
t_r	a time period after day-ahead market clearance and before the delivery time
X, Y	general random variables
x_1	minimum value of x
x_2	maximum value of x
$L_c(p)$	combined loss in the electricity balancing market and the prediction market ($\$$)

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I. Introduction

In a typical day-ahead electricity market, suppliers offer power outputs for each hour of the next day, before the market closure time in the current day. At the operating day, the producers whose realised generation at the actual time of power delivery deviates from their initial submitted bids will be charged for such deviations. Such charges are referred to as *deviation penalties* or *imbalance costs* and depend on the imbalance settlement mechanism of the electricity market as well as the prevailing network supply and demand balance [1].

As the renewable energy share in the power systems is growing rapidly, most of the supporting instruments and incentives (e.g. feed-in-tariffs and power purchase agreements) for these sources are coming to an end based on the new regulations [2]. In such schemes, renewables are expected to take the same balancing responsibilities as the conventional generators in the competitive electricity markets.

The inherent uncertainty associated with wind power forecasting affects the scheduling of Wind Power Producers (WPPs) in the electricity market as the variations of the wind power lead to deviations from their bids. Such significant deviations impose imbalance costs on the WPPs, which comprises a high proportion of their incomes [3]. To address this issue, the WPPS bidding problem has been covered in the literature by maximising the expected profit of the WPPs by considering a probabilistic forecast for the wind power output. For example, in [4] an explicit analytical solution has been derived and in [5] this problem has been formulated as mixed-integer programming and solved numerically. However, risk preferences of power plants impact their bidding strategies when participating in the day-ahead electricity markets [6]. Hence, some works incorporate risk measures as part of the objective function to control the financial risk associated with imbalance costs. As performed in [7]–[9], the most commonly used risk measure is Conditional Value at Risk (CVAR), which is added to the objective function (expected profit) multiplied by a weighting factor, representing the risk adversity of the WPP. In [10], stochastic dominance constraints are included in optimisation problems to manage the negative tail of profit distribution, which outperforms the CVAR method. Moreover, risk assessment of distribution networks due to adverse weather condition is conducted in [11], where associated warnings are provided as the appropriate storage or trading signals for prosumers with renewable sources.

Since all these aforementioned bidding strategies, happen before the gate closure of the day-ahead market, the WPPS fail to exploit new information received closer to the energy delivery time in improving their forecast and alleviating imbalance costs, accordingly.

To cope with this challenge, complementary trading mechanisms, in parallel with participation in the day-ahead market have been proposed in the literature.

In [12] reserve purchasing has been considered in the WPP joint energy and reserve optimal bidding formulation. The key limitation of this mechanism is the price of reserve deployment should be less than the imbalance prices to make the approach beneficial. In [13] combined bidding of the WPP and a compressed air energy storage has been considered. However, it neglects the initial investment costs for installing this storage device from the WPP perspective. As shown in [14], options purchasing, which is a pure financial hedging method, seems more competitive considering the high investment costs of storage installation. In [15] bidding of a group of WPPs, as a joint-venture has been merged to offset deviations. However, it is limited to the same ownership for all the WPPs. Moreover, high correlations among wind farms weaken the performance of the method, as they will not be able to compensate deviations for each other. In [16] the participation of the WPPs in the intraday market has been suggested, which will remain open until one hour before the delivery time and trades between two parties will be settled by the exchange. However, the lack of liquidity and the fact that the volume of trades in this market is restricted by the transmission cables capacities limits this method.

To achieve more flexible solutions, in some studies bilateral option-based mechanisms, including a fixed premium and a flexible rate subject to utilisation of the reserved capacity, have been employed in coordinations between the WPPs and controllable resources. In [17] arrangements with a Demand Response (DR) aggregator has been considered in the scheduling of the WPP. However, DR option contracts prices are adjusted to be beneficial for the WPP in comparison with the real-time market. The problem is only formulated for the WPP profit maximisation and the DR motivation is neglected. This limitation is addressed in [18], where the summation of the avoided costs of the WPP and the thermal generator, as the reserve provider, is maximised. However, it is assumed that without such option contract, the thermal generator will be paid by the day-ahead (spot) price, while it will be subject to real-time imbalance cost for the energy transacted with the WPP and thus deviating from its initial bid. In this regard, a more complete study in this field is [19], where the exposure of both WPP and the conventional supplier to imbalance prices is considered and the Nash equilibrium is achieved to determine the option contract specifications. However, in the generator optimal bidding problem, the reserve utilisation rates of the WPP are based on the historical data, while they are decision variables in the WPP problem.

As noted, above mentioned solutions attempt to hedge the WPPs revenues through the electricity market participants who themselves are subject to the same regulations and network limitations, which restricts the overall performance of the methods. Apart from the electricity market, in [20] an independent insurance product is designed to mitigate the imbalance costs and the premium is calculated, however for the whole annual coverage period.

Financial derivatives such as options, forwards, and future contracts [21], transacted in independent financial markets, enable the selling of products at a fixed price on a certain future date. These instruments have a long history of applications in a broad range of industries, such as oil and gas [22], agriculture [23], seafood [24], and electricity [25] as well. These instruments reduce the price volatility risk. Some producers, however, are subject to the sales volume risk even if the price remains constant, mainly due to unfavourable weather conditions. For example, a farmer's crop dependence on the rainfall levels or the gas demand influenced by the temperature. In this regard, weather derivatives ([26]-[27]) have proven to be an effective risk management tool, by providing payoffs linked to the weather variable being lower or higher than a specified threshold.

The WPPs, obviously, face volume risk due to the resource variations. Wind derivatives [28] are emerging as standard contracts to be traded in exchanges, such as in European Energy Exchange (EEX) [29] to manage wind-related risks. However, since they are available for long-term periods, e.g. weekly or monthly and derive their value from accumulative wind index in these periods, they might not be applicable for hedging the WPP

TABLE I
COMPARISON OF THE WPP RISK MANAGEMENT METHODS

Method	Limitations/Features	Trading Venue
Incorporating risk measures in optimal bidding strategies [7]–[10]	Before the market gate closure	Electricity Market
Joint-operation with storage [13]	High investment cost	Electricity Market
Reserve purchasing [12]	Dependence on the reserve prices	Electricity Market
Joint-offering of WPPS [15]	High correlation between WPPS	Electricity Market
Intraday market [16]	Weak liquidity, transmission congestion	Electricity Market
Option-based bilateral contracts [17]–[19]	Conflict of the counterparties' incentives	Electricity Market
Electricity derivatives [25]	Mainly hedge price risk	Financial Market
Wind derivatives [28]	Long-term period accumulative payoff	Financial Market
Insurance Products [20]	Long-term coverage period and associated premium	Financial Market
Prediction markets	Hourly payoff linked to the future value of the wind power	Financial Market

hourly imbalance costs. Prediction markets, on the other hand, are able to fulfil this gap. Table I categorises and compares the above-mentioned methods and summarises their main features and limitations.

Prediction markets [30] are a type of future markets where participants bet on the outcome of an event and trade contracts (shares) associated with their forecast. While prediction markets have existed in centralised form for many years, blockchain technology facilitates the running of these markets in a decentralised, and thus a more accessible and flexible form. These features underpin the application considered in this paper. Moreover, the spot prices in these transparent liquid prediction markets serve as an accurate forecast signal for the system operators.

In this paper, a trading strategy in such a prediction market has been formulated to compensate for the imbalance costs in the electricity market by combining the payouts of the two venues. The authors proposed the general idea in [31], by introducing blockchain-hosted prediction markets as a forecasting and hedging tool to manage the intermittency of renewable energy sources. To date, no study has investigated the application of prediction markets to hedge against WPP imbalance costs. The schematic representation of this idea is provided in Fig. 1. The main features of the novel method presented in this work are as below:

- The approach is straightforward for the WPP to implement, as it only requires the prediction of the WPP output which is a regular task of the WPP and is not concerned with any specific pricing of the future contracts,

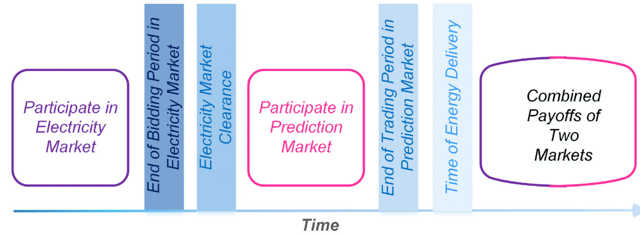

Fig. 1. Schematic representation of combined trading in the electricity market and prediction market over time.

- Trading in the prediction market can take place in any time frame before the actual power delivery time and even after the closure of the day-ahead electricity market. Therefore, the WPP can benefit from the new information arriving as time progresses.

The remainder of this paper is structured as follows: Section II describes the methodology of the work and outlines a trading strategy for the WPP which leads to the reduction of financial risk. Section III provides a number of case studies to demonstrate the performance of the proposed hedging method. Finally, Section IV concludes the paper.

II. METHODOLOGY

The idea behind this hedging methodology proceeds from noting that, since both the electricity market and the prediction market are future markets whose payouts depend on the realised wind power, by taking opposite positions in these markets payouts in one market compensate for a loss in the other. While the proposed method can be applied to any producer with a stochastic output with a known PDF, WPPS are the focus of this paper, because of the high degree of uncertainty in the forecasting of their output, which exposes them to more deviation losses.

In this section, first, the models of the day-ahead electricity market and the prediction market are provided. Then, the combination of the imbalance costs in the electricity market and the payouts in the prediction market are formulated. Finally, trading strategies aimed at limiting the loss values are developed.

A. Electricity Market Model

In the following parts, first, the imbalance settlement mechanism for deviations is explained, then the WPP's revenue is formulated and the imbalance cost function is derived.

1) Imbalance Settlement Mechanism: Generally, deviation penalty prices in real-time depend on the supply and demand balance of the system and reflect the cost of the reserve for compensating such deviations. In this study, a dual price settlement mechanism is considered to quantify the imbalance costs, which is common in most European electricity markets and is employed in [9], [12], [15]. In this mechanism, the imbalance settlement price for underproduction, q, and overproduction, λ, is different and only deviations in the opposite direction of the system imbalance would be penalised and the deviations which offset the system imbalance will be settled with the day-ahead market price, r. In this mechanism, the imbalance cost function,

$L_e(p)$, is defined as:

$$L_e(p) = \begin{cases} P_{max} q(p - c^*) & p \le c^* \\ P_{max} \lambda(p - c^*) & p \ge c^* \end{cases} \tag{1}$$

which implies that if the WPP delivers less energy than already offered, will be penalised by $q(p - c^*)$ and if it produces more than its initial offer, will be paid $\lambda(p - c^*)$. Note that, usually $\lambda > 0$ meaning that the overproduction will be payable, but with a price less than r. Moreover, since WPPs are equipped with power curtailment facilities, they avoid overproduction penalties. However, to generalise the idea and demonstrate the symmetry of the hedging method for underproduction and overproduction situations, this type of risk is covered in our methodology as well.

2) WPP's Revenue and Imbalance Cost Functions: To quantify the revenue of the WPP, we consider a time period, t_r, after the day-ahead market clearing, when the day-ahead price, r, is known. The WPP's expected revenue in this period, is a combination of a fixed the day-ahead market revenue, $rc^* P_{max}$ and the expected value of the imbalance cost function, $L_e(p)$ (from (1)), as given by:

$$E[J|r, t_r] = rc^* P_{max} + E[L_e(p)|r, t_r] \tag{2}$$

The optimal day-ahead bid value which maximises the expected revenue of the WPP, when submitting before the gate closure, can be determined through various approaches. However, to generalise the idea, the proposed method in this work is not confined to a specific bidding strategy. Therefore, it has been assumed that the WPP has submitted an arbitrary bid, with a hypothetical value, which is denoted by c^*, to the day-ahead electricity market.

It should be noted that since trading in the prediction market takes place after the day-head market clearance, i.e., at the time t_r, when the day-ahead electricity market price, r, is revealed, so there is no uncertainty about r in the proposed hedging model. However, regarding the real-time balancing market, there are two uncertain parameters, which are the real-time imbalance prices, i.e., λ, and q. These two parameters have been modelled as random variables with given probability distributions conditioned on the information available at the time t_r.

3) Imbalance Prices: In this work, the WPP is considered as a price taker in the real-time balancing market, since its capacity is negligible in comparison to the whole market generation capacity. Therefore, its participation in the market does not affect the clearing prices. Some studies e.g. [4], [12], assume that real-time prices are independent of the WPP power production, and consider only the expected values of these prices, as constant exogenous parameters in the model.

However, the system aggregated wind power production, coming from all the wind power plants, can influence the overall supply level in real-time. Since the local WPP experiences the same wind conditions in the nearby geographical area, a correlation exists between the WPP output and the real-time imbalance prices. Note that due to the spatial correlation among wind power plants installed in a region, the WPP output and the imbalance prices are correlated. However, if for any reason that is not related to the weather, a wind power plant curtails its production, e.g., for maintenance, or due to the congestion in power system lines, this limitation would not impact the prices since the capacity of a single WPP is negligible in comparison to the whole system generation capacity (the WPP is a price-taker in the market). Therefore, while a causal link does exist between the underlying weather system and the prices, the correlation between the single WPP output and the prices does not necessarily imply causality.

For considering such correlation, we adopt the approach employed in [32] and [33]. By considering the joint probability distributions of p with q and λ, the expected value of the WPP revenue in (2) can be expressed as:

$$\begin{aligned} E[J|r, t_r] &= rc^* P_{max} \\ &+ P_{max} \int_{q_{min}}^{q_{max}} \int_0^{c^*} q(p - c^*) f_{Q,P|r,t_r}(q, p) dq dp \\ &+ P_{max} \int_{\lambda_{min}}^{\lambda_{max}} \int_{c^*}^{1} \lambda(p - c^*) f_{\Lambda,P|r,t_r}(\lambda, p) d\lambda dp \end{aligned} \tag{3}$$

By following the property relating joint probabilities to conditional probabilities, given by:

$$f_{X,Y}(x, y) = f_{X|Y}(x|y) f_X(x) \tag{4}$$

Equation (3) can be expressed in terms of conditional expectation of imbalance prices with realisation of the WPP output as:

$$\begin{aligned} E[J|r, t_r] &= rc^* P_{max} \\ &+ P_{max} \int_0^{c^*} E[Q|p, r, t_r](p - c^*) f_{P|t_r}(p) dp \\ &+ P_{max} \int_{c^*}^{1} E[\Lambda|p, r, t_r](p - c^*) f_{P|t_r}(p) dp \end{aligned} \tag{5}$$

Therefore, we can formulate the imbalance cost function in (1) as:

$$L_e(p) = \begin{cases} P_{max} E[Q|p, r, t_r](p - c^*) & p \le c^* \\ P_{max} E[\Lambda|p, r, t_r](p - c^*) & p \ge c^* \end{cases} \tag{6}$$

Equation (6) states that when the WPP is in underproduction status, the higher the deviation, the greater is the imposed penalty price and in an overproduction status, the greater the deviation, the lesser would be the payment price dedicated to the surplus generation.

For any given distribution, expected real-time imbalance prices, conditioned on wind power production and day-ahead clearance price in (6), i.e., $E[Q|p, r, t_r]$ and $E[\Lambda|p, r, t_r]$, can be computed through numerical integration. However, to quantify them by closed-form expressions, one possible case employed in [32] and [33], is to assume that the wind power and imbalance prices follow a bivariate Gaussian distribution. Another approach is proposed in [32], where a convex quadratic function is considered for the relationship between imbalance prices and wind power, resembling the cost function of the thermal generators, compensating the wind deviations in the system. The correlation coefficients based on empirical data are also investigated in [33], leading to multivariate asymmetric student t-distributions. These approaches agree on the fact that a negative correlation exists between imbalance prices and wind outputs. In this paper, negatively correlated bivariate normal distributions are considered, which lead to the expected values of imbalance prices given by (7) and (8).

$$E[Q|p, r, t_r] = \mu_q + \rho_{qp}\frac{\sigma_q}{\sigma_p}(p - \mu_p) \tag{7}$$

$$E[\Lambda|p, r, t_r] = \mu_\lambda + \rho_{\lambda p}\frac{\sigma_\lambda}{\sigma_p}(p - \mu_p) \tag{8}$$

where $\mu_q \geq r$, $\mu_\lambda \leq r$ and $\rho_{qp} \leq 0$, $\rho_{\lambda p} \leq 0$, reflecting the negativity of correlations.

B. Prediction Market Model

The prediction market platform considered in this work is based on Augur [34], which is a set of smart contracts running on the Ethereum platform. For the details of the blockchain layer, responsible for recording the transactions and the procedure of clearing the market, we refer to [31] and [35]. Regarding the methodology of this paper, since the issue is considered from the WPP's perspective, it suffices to focus on the trading side of the prediction market and to model the payout functions.

Prediction markets in a platform such as Augur are available in three forms: *binary* markets, also known as *yes/no* markets, *categorical* markets for those events with more than two and less than eight possible outcomes, and finally *scalar* markets, also known as the numerical range. Here, we employ scalar markets, which provide the opportunity to speculate on the direction of a variable's value within a certain range.

In this section, first, the settlement mechanism of Augur scalar markets is introduced. Then, the payouts of the WPP in such market is formulated and finally, the method of pricing the shares in this market is discussed.

1) Scalar Market: The scalar prediction market type [34] is applicable for speculating on the future value of a variable in a range specified by a lower limit and an upper limit. This market offers two kinds of contracts (shares): *short* share, which pays out more when the outcome is closer to the lower limit and *long* share, which pays out more when the outcome is closer to the upper limit.

The payout functions of each *short* share and *long* share are calculated based on a linear function, stated in (9) and (10), respectively, as $H(x)$ and $G(x)$:

$$H(x) = \begin{cases} 1-k & x \leq x_1; \\ (x_2 - x)(1-k)/(x_2 - x_1) & x_1 \leq x \leq x_2; \\ 0 & x \geq x_2. \end{cases} \tag{9}$$

$$G(x) = \begin{cases} 0 & x \leq x_1; \\ (x - x_1)(1-k)/(x_2 - x_1) & x_1 \leq x \leq x_2; \\ 1-k & x \geq x_2. \end{cases} \tag{10}$$

where $x \in [x_1, x_2]$ is the actual outcome of the random variable X.

For the application addressed in this methodology, a prediction market is considered, which is asking: *What will be the* WPP*generation in the range [0,1] at a certain time of power delivery at the operating day?* In the aforementioned prediction market, the random variable to be forecasted by the participants is the per-unit value of the wind power with realisation p and x_1 and x_2 are 0 and 1, respectively. According to the equations (9) and (10), *net* payout functions of n shares with price m, are given by:

$$H^n(p) = n(1-p)(1-k) - nm \tag{11}$$

$$G^n(p) = np(1-k) - nm \tag{12}$$

where $m \in [0, 1]$, and obviously can have different values for short and long shares. Note that, since the medium of exchange in Augur platform is DAI, which is a stable coin dollar-pegged cryptocurrency [36], for the sake of simplicity, its value is assumed equivalent to the US dollar, as the currency in the electricity markets and therefore, exchanging currencies is avoided in the following formulations.

2) Utility Indifference Pricing of Shares in Prediction Market: Since the generation of the WPP, and consequently the payouts in the prediction market are random variables, the acceptable price of the shares is influenced by the expected value of the payouts. By considering the expected value of p as $E[p|t_r] = \mu_p = \int_0^1 p f_{P|t_r}(p)dp$, the maximum price of a *long* share equals $\mu_p(1-k)$ and the maximum price of a *short* share equals $(1-\mu_p)(1-k)$. This price results in a net expected gain of zero, indicating a fair bet [37]. However, this pricing policy is only valid for risk-neutral participants. In practice, different participants have different attitudes towards risk, reflected by their utility functions [38] and therefore, they might offer prices lower or higher than this value.

Risk-averse participants have concave utility functions and offer prices lower than the expected value of the payouts while risk-seeking participants have convex utility functions and offer prices higher than the expected value of the payouts. In other words, each participant has a specific equilibrium price which indicates indifference condition for them and is a nonlinear function of the number of shares [39].

For a risk-averse participant in the prediction market, we assume a utility function $U(w) = -\exp(-bw)$. Indifference utility pricing of the short shares in the scalar prediction market can be achieved by solving :

$$\int_0^1 \exp\left(-b(w_0 + H^n(p))\right) f_{P|t_r}(p)dp = \exp(-bw_0) \tag{13}$$

where the expected utility of the payoffs, $w_0 + H^n(p)$, is equal to the utility value of an initial wealth of w_0. By some algebraic manipulations to (13), the indifference price of the short shares can be expressed as:

$$m = 1 - k - \frac{1}{bn}\log\left(\int_0^1 \exp\left(bn(1-k)p\right) f_{P|t_r}(p)dp\right) \tag{14}$$

Likewise, the indifference price of the long shares is given by:

$$m = -\frac{1}{bn}\log\left(\int_0^1 \exp\left(-bn(1-k)p\right) f_{P|t_r}(p)dp\right) \tag{15}$$

As noted, indifference price is a descending nonlinear function of the number of shares, n and depends on the PDF of forecasted

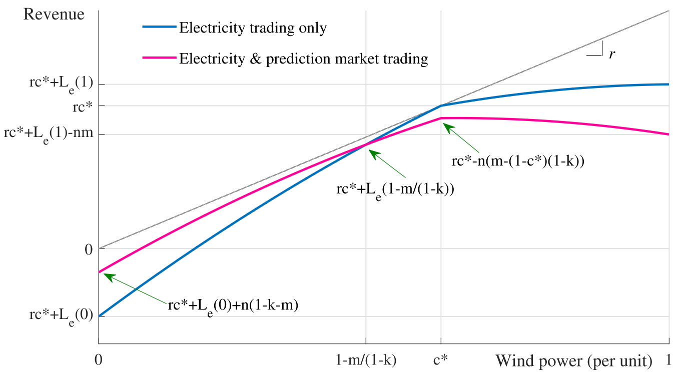

Fig. 2. Comparison of the WPP revenue curves with and without buying short shares in prediction market ($P_{max} = 1$ MWh).

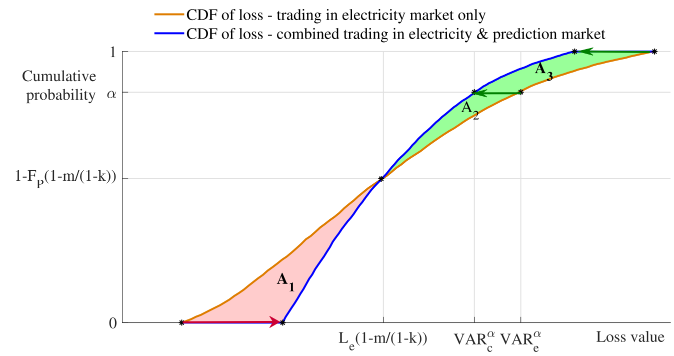

Fig. 3. Effect of trading in prediction market on the probability distribution of the WPP loss.

wind power output, prediction market settlement fees, k and the degree of risk adversity of the participant, b. The more risk-averse is the participant, the less he would price the shares in the prediction market, accordingly.

C. Combination of Trading in Electricity Market and Prediction Market

To hedge against deviation losses in the electricity market, we propose that to hedge against deviation losses in the electricity market, the WPP should take the opposite position in the prediction market in comparison to the electricity market. This way, the payouts in the prediction market can compensate for the deviation losses in the electricity market. Therefore, when the WPPs are subject to the *underproduction* loss in the electricity market, they should buy *short* shares in the prediction market. Similarly, when they are subject to *overproduction* loss, they should buy *long* shares.

It should be noted that the main contribution of this work, is to provide a vision of how a prediction market has the potential to hedge against imbalance costs, which serves as the first proposal for implementing this idea. Therefore, to show this principle, it suffices to keep the assumptions of bivariate normal distributions for the correlations between the wind power outputs from Section II-A3 as well as the assumption of the exponential utility function for the WPP from Section II-B2, when we model the WPP electricity revenue and his risk preferences in this section.

In our model, there are two sources of revenue for the WPP. One source comes from the electricity market, consisting of a fixed part associated with the day-ahead market, i.e., rc^*P_{max}, and a stochastic part associated with the balancing market, according to (6). The other source comes from the payoffs in the prediction market, which is also stochastic and is expressed in (11). Combining these two revenue streams leads to $rc^*P_{max} + L_e(p) + n(1-p)(1-k) - nm$.

In Fig. 2, this combined revenue is shown in comparison with the revenue from exclusively electricity trading, which is $rc^*P_{max} + L_e(p)$. Note that the price of shares is assumed as m and $P_{max} = 1$ MWh. in this figure. As demonstrated, wind power values less than $1 - m/(1-k)$ result in positive net payouts in the prediction market, thus increasing the WPP revenue, while higher wind power values reduce the revenue. Therefore, strategic purchasing of shares is required to exploit the hedging potential of this method.

Likewise, buying long shares result in a combined value of $rc^*P_{max} + L_e(p) + np(1-k) - nm$ with symmetrical features.

1) Effect of Trading in Prediction Market on Statistical Measures of the Loss Function: Excluding the constant value of rc^*P_{max} from the revenue curves, which is explained based on Fig. 2, gives the corresponding loss values. Investigating the CDFs of loss functions with and without trading in the prediction market is shown in Fig. 3. It demonstrates that buying short shares in the prediction market while the WPP is subject to underproduction loss results in the following features:

- The loss values will be confined in a narrower range and the standard deviation (STD) of loss will be reduced by trading in the prediction market.
- Value at Risk (VAR): By definition, at a confidence level of α, the value of loss will be greater than VAR^α with a probability of $1-\alpha$. As shown in Fig. 3, by trading in the prediction market the value of VAR^α will be reduced. This feature is valid for $\alpha \in [1 - F_{P|t_r}(1 - m/(1-k)), 1]$. This range depends on the price of shares in the prediction market, denoted by m and provides acceptable cover to most investors, as the common value of α is around $90\% - 95\%$, resulting in high values of m, which are competitive in prediction markets.
- Conditional Value at Risk (CVAR): By definition, CVAR is the expected value of the loss exceeding VAR^α. As shown in Fig. 3, by trading in the prediction market the value of CVAR will be reduced corresponding to the area denoted by A_3.
- The expected value of loss can be increased or decreased corresponding to the area $A_2 + A_3 - A_1$. In other words, A_1 increases the expected value of loss while $A_2 + A_3$ results in a reduction.

Buying long shares when the WPP is subject to overproduction loss results in symmetrical features.

D. Trading Strategies in the Prediction Market to Reduce Deviation Losses in Electricity Market

In this section, two possible trading strategies in the prediction market are proposed: 1) *minimising the maximum of loss* and 2) *utility indifference strategy*. Then, the procedure for determining the optimal strategy is provided as a trade-off between these two strategies.

1) Minimising the Maximum of Loss: The WPP's total loss consists of imbalance costs in the electricity market, as expressed in (6) and payoffs in the prediction market, as expressed in (11). Combining these two sources of loss leads to (16):

$$L_c(p) = L_e(p) + n(1-p)(1-k) - nm \tag{16}$$

As can be inferred from Fig. 2, the maximum loss in the electricity market happens at $p = 0$ while the maximum loss in the prediction market happens at $p = 1$. Combining the payouts of two venues, decreases the loss value at $p = 0$ while increases the loss value at $p = 1$. Therefore, minimising the maximum loss happens when the combined payouts at these two points are equal, as given by:

$$L_e(0) + n(1-k) - nm = L_e(1) - nm \tag{17}$$

Equation (17) is valid for $L_e(0) < 0$ and $L_e(0) < L_e(1)$, implying that the maximum imbalance cost is due to underproduction. Substituting the values of $L_e(0)$ and $L_e(1)$ from (6), the corresponding number of shares for the min max strategy is given by:

$$n^* = P_{max}((1-c^*)E[\lambda|1, r, t_r] + c^*E[Q|0, r, t_r])/(1-k) \tag{18}$$

The value of n^* obtained from (18) results in minimising the maximum loss while achieving the minimum standard deviation by limiting the loss values in the narrowest possible range.

Likewise, n^* when the maximum imbalance cost stems from overproduction ($L_e(1) < 0$ and $L_e(1) < L_e(0)$) is given by:

$$n^* = P_{max}((c^*-1)E[\lambda|1, r, t_r] - c^*E[Q|0, r, t_r])/(1-k) \tag{19}$$

2) Utility Indifference Strategy: As can be inferred from (18), the number of shares minimising the maximum loss, n^*, is independent of the price of shares.

We consider that the WPP has already traded in the day-ahead electricity market and then seeks to hedge against the risk of imbalance costs through the prediction market. Indifference condition for this WPP suggests that the expected utility after trading in the prediction market should be equal to the initial expected utility of imbalance costs in electricity market. By following the approach explained in Section II-B2 and assuming that the WPP has the same exponential utility function, we get the indifference price of short shares given by:

$$m^*(n) = 1 - k + \frac{1}{bn}\log\left(\int_0^1 \exp\left(-bL_e(p)\right)f_{P|t_r}(p)dp\right) - \frac{1}{bn}\log\left(\int_0^1 \exp\left(bn(1-k)p - bL_e(p)\right)f_{P|t_r}(p)dp\right) \tag{20}$$

Likewise, the indifference price when buying long shares is given by:

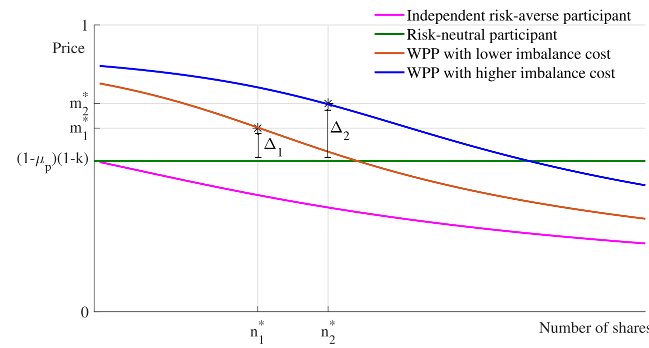

Fig. 4. Utility indifference pricing of short shares in prediction market by various participants.

$$m^*(n) = \frac{1}{bn}\log\left(\int_0^1 \exp\left(-bL_e(p)\right)f_{P|t_r}(p)dp\right) - \frac{1}{bn}\log\left(\int_0^1 \exp\left(-bn(1-k)p - bL_e(p)\right) f_{P|t_r}(p)dp\right) \tag{21}$$

At each price of m, the corresponding number of shares satisfying the indifference condition can be achieved by solving $\arg(m^*(n) = m)$. Indifference prices serve as the upper bound of pricing in the prediction market from the perspective of the participants.

Fig. 4 provides a graphical presentation of this pricing method. It shows that the maximum price from the perspective of a risk-neutral participant is always the expected value of one share payoff, regardless of the number of shares, which leads to zero expected gain. However, the WPP would even neglect a certain amount of expected gain, as the cost of hedging against maximum electricity imbalance loss, similar to any insurance purchasing policy. As stated in [40], "*hedging means that a decision maker will opt for a more costly solution, if this reduces the negative consequences of possible adverse futures, instead of choosing a cheaper solution that, however good in most futures, may lead to a heavy loss in a particular scenario.*" For example, by considering the orange curve, n_1^* minimises the maximum loss and by purchasing these number of shares at the maximum price of m_1^*, the lost expected revenue would be $n_1^*\Delta_1$. Comparing the blue and orange curves in Fig. 4, also shows that when the WPP is subject to higher imbalance costs, the maximum acceptable price of shares with the aim of hedging increases.

3) Optimal Trading Strategy: In this section, an optimal trading strategy is provided through a step-by-step procedure, illustrated in Fig. 5. First, according to (6) in the electricity market, the WPPs realise whether the maximum possible loss stems from underproduction or overproduction. Then, they should follow a symmetrical procedure in both situations. As stated in this flowchart, based on the price of shares available, the WPP decides for choosing between *min max* strategy and *utility*

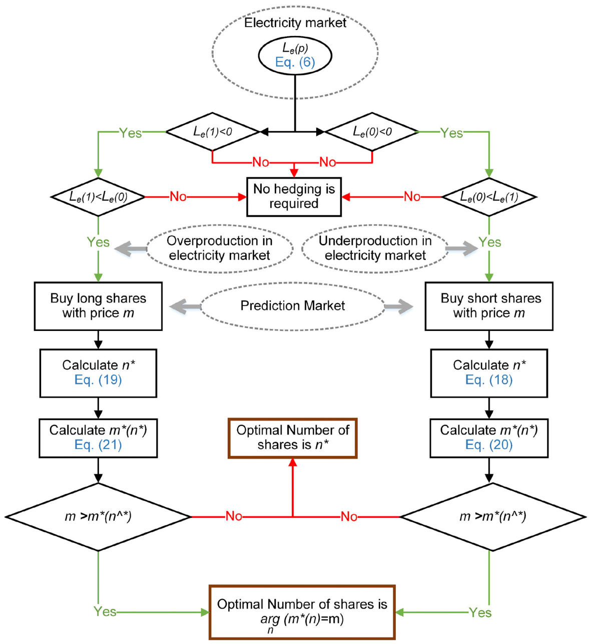

Fig. 5. A flowchart showing the hedging strategy of the WPP.

indifference strategy, which are described in section II-D1 and II-D2, respectively.

First, the number of shares minimising the maximum loss, n^* is calculated from (18) for underproduction and (19) for overproduction. Then the indifference price at these values, $m^*(n^*)$, is calculated from (20) and (21), respectively. If the current price of shares in the prediction market, denoted by m, is lower than these indifference prices, the optimal number of shares to be purchased is n^* and otherwise $\arg(m^*(n) = m)$. Such trading strategy ensures that the maximum hedging against worst-case loss is achieved while not exceeding the utility indifference price. Note that the uncertainty associated with imbalance prices, λ and q, are reflected through their probability distributions by incorporating $E[Q|p, r, t_r]$, and $E[\Lambda|p, r, t_r]$ in equations (6), (18), (19), (20), and (21), which contribute to determining the optimal trading strategy in Fig. 5.

III. Results

This section provides a number of case studies that show how the trading strategies proposed in section II can be applied and the effects of trading in prediction market on the risk measures. The scripts implementing these examples are available in a persistent online repository at [41].

We assume that the forecasted output of the WPP, follows a normal probability distribution. This assumption is legitimate because the time frame of our case study is short-term and in short-term probabilistic forecasting methods of random variables, it is a common practice to assume that the errors of spot (point) forecasts follow a normal distribution and a wide variety of the methods devised for time-series forecasts exploit this assumption [42]. This well stands for short-term forecasts of the wind power generation, as has been considered in [43], [44], where SVR (Support Vector Regression) has been employed for the spot forecasts while the error term follows a normal distribution with a zero-mean. Therefore, we consider a normal distribution with a mean of 0.45, and for the production of the WPP, we have used truncated distribution, which results in $\mu_p = 0.468$ per unit and a standard deviation of $\sigma_p = 0.23$.

Note that the distribution form of the WPP generation does not influence the concept of the proposed hedging method, as regardless of this distribution, by taking the opposite positions in the two markets, the revenue curve shown in Fig. 2 would be turned around the point $1 - m/(1-k)$, which, consequently, reduces the risk. This feature is also evident from Fig. 3, where the CDF of loss would be turned around the point, $L_e(1 - m/(1-k))$, which improves the risk measures, as explained in Section II-C. However, the change of the distribution form would impact the strategy of trading in the prediction market, i.e., the volume of shares (according to (18) and (19)), and the price of shares (according to (20) and (21)).

The maximum production of the WPP is assumed $P_{max} = 1$ MWh and the trading strategies are investigated for a single time period of one hour. To allow us to show in practice how the proposed method would work with some kind of numerical data, for the relationship of imbalance prices and day-ahead market price, we have used the estimations provided in [45] for the Nordic market. These estimations are also consistent with the average values of 13 Nov 2019 for Denmark (area 1), based on the data available in [46]. Day-ahead market clearing price is considered $r = 50$ \$/MWh. The deviation penalty prices follow normal distributions which their expected values are expressed as $\mu_q = 1.05r$ and $\mu_\lambda = 0.95r$. Standard deviations have been considered as $\sigma_q = \sigma_\lambda = 30$, which are correlated with the wind power with a coefficient of $\sigma_{qp} = \sigma_{\lambda p} = -0.25$. As reported in [33], the wind-price correlation takes a value in the range of $[-0.12, -0.56]$, depending on the wind power penetration level in various systems. Note that any changes in the assumed values will result in different amounts of imbalance costs, which should be hedged against. Therefore, the volume of purchased shares in the prediction market may take different values, accordingly: based on (18) and (19), for calculating the number of shares; and based on (20) and (21), for calculating the price of shares. However, the interpretation of optimal strategy would still follow the flowchart in Fig. 5.

The utility function of the WPP is considered with the negative exponential form of $U(w) = -exp(-bw)$, which is a standard function for modelling the risk averse behaviour of investors, as has been used in [38], [47]. This is also applicable for the case of a risk-averse WPP, as employed in [48]. The degree of risk adversity is reflected by parameter b, which is assumed 0.05. The electrical bid submitted to day-ahead market is assumed $c^* = 0.6$ and the settlement fee of trading in the prediction market is assumed $k = 1\%$. The effect of changing the day-ahead bid and risk adversity degree is further explored in Section III-C.

A. *Effect of Price and Number of Shares on the Hedging Performance*

Fig. 6 shows the effect of purchasing shares in the prediction market on the loss profile of the WPP by varying the price and the number of shares. Prices are selected as 0.53 is equal

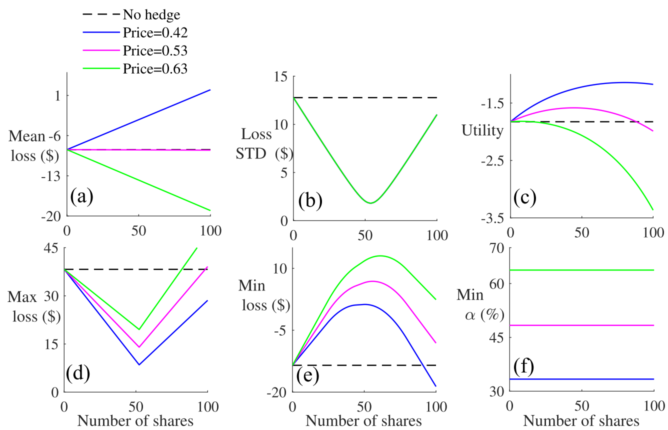

Fig. 6. Effect of price and number of shares in prediction market trading on: a) Mean of loss, b) Standard deviation of loss, c) Utility value, d) Maximum loss value, e) Minimum loss value and f) Minimum confidence level (α).

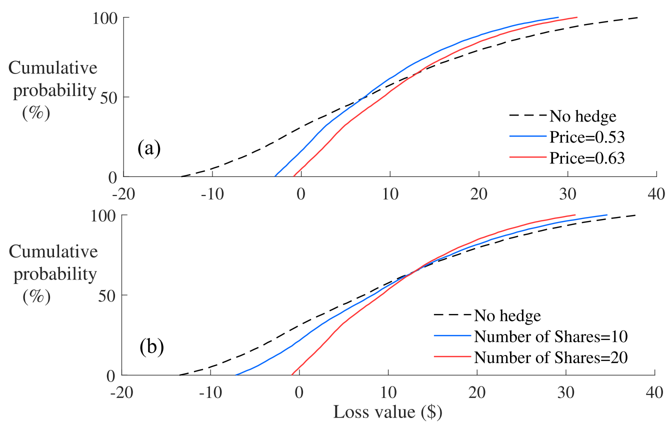

Fig. 7. Comparing the CDF of hedged loss by trading in prediction market against unhedged case: a) the effect of price and b) the effect of number of shares.

to the expected value of the payoffs in the prediction market and therefore does not affect the mean of loss. A price higher and a price lower than this, as 0.63 and 0.42 are considered, respectively. The mean, max and min of loss depend on both price and number of shares. The standard deviation of loss only depends on the number of shares, as the price shift all the values equally. The confidence level support is only affected by the price. As clear from Fig. 6(b) and Fig. 6(d), the number of shares resulting in minimising the maximum loss and standard deviation is 52.25, which is consistent with (18).

Hedging performance is also investigated by noting that how the shape of the CDF of loss function changes with a higher or lower number of shares and the price of shares. In Fig. 7(a) the number of shares is kept constant while the price is varied and in Fig. 7(b) the price is constant to see the effect of the various number of shares. Such investigation, help clarify the resulting effects on risk measures, which is provided in Fig. 6.

B. Hedging Against Underproduction Loss

To simulate the scenario that the maximum loss stems from the underproduction penalty, it is supposed that the WPP has submitted a bid of $c^* = 0.6$ per unit to the day-ahead electricity market. According to (18), the number of shares minimising the maximum loss is 52.2 which corresponds to the indifference price of 0.58, from (20). This price is about 10% higher than the indifference price of a risk-neutral trader, which is $(1-k)(1-\mu_p) = 0.526$.

TABLE II
OPTIMAL TRADING STRATEGY ACCORDING TO DIFFERENT PRICES IN PREDICTION MARKET (MAXIMUM UNDERPRODUCTION CASE)

Item	Unhedged	Hedged		
		Min Max	Utility	Utility
Price	-	0.553	0.605	0.631
No.shares	-	52.2	34.34	15.1
VAR	$27.26	$12.73	$18.95	$23.9
CVAR	$3.18	$1.43	$2.17	$2.82
STD	$12.73	$1.84	$4.9	$9.23
Max Loss	$38.2	$15.39	$25.02	$32.8
Mean Loss	$8.6	$9.8	$ 11.2	$10.15

To identify the optimal trading strategy, based on the flowchart in Fig. 5, three situations of the prediction market order book is considered with prices 0.553, 0.605 and 0.631, which are all higher than risk-neutral price. As Table II shows, in all cases the risk measures including VAR, CVAR and STD are improved compared to the unhedged case and the maximum of loss is reduced, however, at the expense of an increase in the mean of loss. The optimal trading strategy is determined in order to keep this increase in the mean of loss consistent with the risk-preferences of the WPP.

The first price result to choose the min max strategy as the optimal decision because according to the indifference utility condition the price is acceptable while the other two prices cause the number of shares to be revised according to the indifference condition, leading to higher risk measures VAR, CVAR and STD and higher maximum loss, indicating partial hedging due to lower purchased number of shares.

C. Effect of Electricity Bid and Risk-Aversion on Trading Strategies in Prediction Market

Fig. 8 is provided to investigate the effect of the electricity bid that already has been submitted to the day-ahead electricity market, c^*, on optimal trading strategy in the prediction market. As shown in this figure, the higher the bid submitted to the electricity market, so the WPP is subject to higher underproduction loss and consequently, the number of shares needed to minimise the maximum loss, n^* from (18) increases. At the same bid values, the price cap, m^*, corresponding to n^*, derived from (20) increases, which allows the purchasing of shares at more competitive prices. This feature proves the feasibility of the proposed optimal strategy as a hedging method.

Moreover, this figure also shows the effect of the risk-adversity degree of the WPP reflected by parameter b in their utility function. The more risk-averse is the WPP, the higher is their curve of indifference pricing, indicating that they are willing to neglect a higher amount of their expected revenue in order to avoid risk. However, the min max strategy is independent of risk-aversion degree.

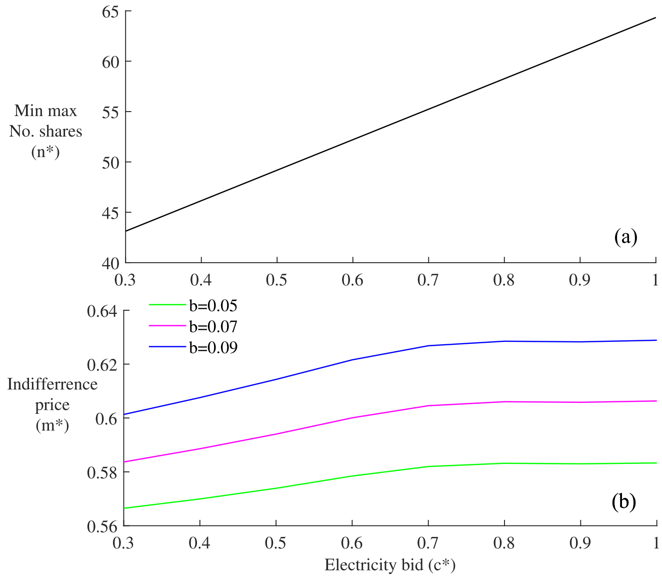

Fig. 8. Effect of electrical bid and risk-adversity on the prediction market trading strategies a) number of shares in min max strategy b) price in utility indifference strategy.

TABLE III
OPTIMAL TRADING STRATEGY ACCORDING TO DIFFERENT PRICES IN PREDICTION MARKET (MAXIMUM OVERPRODUCTION CASE)

Item	Unhedged	Hedged		
		Min Max	Min Max	Utility
Price	-	0.477	0.486	0.51
No.shares	-	20.94	20.94	18.1
VAR	\$26.94	\$24.54	\$24.73	\$25.28
CVAR	\$3.4	\$2.89	\$2.9	\$2.94
STD	\$9.74	\$7.57	\$7.57	\$7.72
Max Loss	\$43.03	\$32.30	\$32.50	\$34.14
Mean Loss	\$12.78	\$13.12	\$ 13.31	\$13.49

D. Hedging Against Overproduction Loss

To simulate the scenario that the maximum loss stems from the overproduction penalty, it is supposed that the WPP has submitted a bid of $c^* = 0.35$ per unit to the day-ahead electricity market. We have changed $\mu_\lambda = -1.05r$, which leads to the maximum overproduction case. Note that this is just a hypothetical case to generalise the proposed hedging strategy. Usually, μ_λ takes a positive value less than r and most WPPs are equipped with power curtailment method to avoid the overproduction penalty.

According to (19), the number of shares minimising the maximum loss is 20.94, which corresponds to an indifference price of 0.494 from (21). This price is about 7.8% higher than the indifference price of a risk-neutral trader, which is $(1-k)\mu_p = 0.463$. To identify the optimal trading strategy based on Fig. 5, three situations of the prediction market order book are considered with prices 0.477, 0.486 and 0.5, which are all higher than the risk-neutral price. As Table III shows in all cases the risk measures including VAR, CVAR and STD are improved compared to the unhedged case and the maximum of loss is reduced, however, at the expense of an increase in the mean of loss. The optimal trading strategy is determined in order to keep this increase in the mean of loss consistent with the risk-preferences of the WPP.

The first and second prices result to choose the min max strategy as the optimal decision because according to the indifference utility condition the price is acceptable. The third price, cause the number of shares to be be revised according to the indifference condition, leading to higher risk measures VAR, CVAR and STD and higher maximum loss, indicating partial hedging due to lower purchased number of shares.

IV. CONCLUSION

Trading in the prediction market allows wind power producers to manage the financial risk of trading in the day-ahead electricity market due to imbalance costs. To this end, positions taken in the two markets should be opposite of each other, so that the payouts in the prediction markets compensate for the deviation losses in the electricity market.

Wind power producers can strategically trade in prediction markets to exploit this hedging potential and minimise the worst-case loss while being consistent with their risk preferences reflected by their utility values. In this paper, the loss profile of the wind power producer is optimally shaped when combined with trading in prediction markets in order to improve various risk measures. While the findings from this work suggest the benefit of prediction markets from the perspective of a wind power producer, other parties can gain from the accurate forecast signal that these markets also provide.

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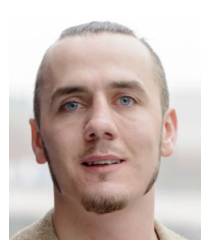

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