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Towards the Use of Blockchain Prediction Markets for Forecasting Renewables

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***Abstract*—This paper proposes and discusses the idea of using nascent blockchain hosted prediction markets as a decentralised crowd sourcing method for renewable energy forecasting. This method is further used as a risk management and hedging tool against volatility in weather variables they depend on. While existing approaches have been centralised by nature, with limited sources of input data and models, prediction markets allow anyone to participate in forecasting by betting on an outcome and earning profits for correct results. Since they have mercenary motivations, these participants are most likely to provide reliable and accurate information. Moreover, renewable energy producers can participate in these prediction markets to hedge against low income periods of time due to poor weather conditions. This paper delivers a conceptual framework to exploit prediction markets in a blockchain platform with the aim of forecasting and hedging of renewable energy sources. The potential financial gain from applying this approach has been demonstrated through a case study for a typical small wind power producer.**

I. Introduction

RENEWABLE energy is expanding in the power sector. Its global capacity grew to around 2,378 GW in 2018, accounting for more than 33% of the world total installed power generating capacity [1].

At such high penetration level, uncertainty in the output power of volatile weather-based sources, such as wind and solar, cause electrical systems to face various technical and economical challenges such as reducing stability [2] and reliability [3] and increasing capacity reserve requirements [4]. To overcome these challenges, it is timely to develop improved prediction models to make these sources more forecastable. Inaccuracy in renewable energy forecasting brings significant costs to wind generators due to compensating imbalances in electricity markets and this could be as much as 10% of the total wind generator incomes from selling energy, based on the assessment provided in [5].

On the other side, from system operator point of view, prediction errors result in costs associated with daily unit commitment/economic dispatch decisions. Every percentage point of improvement in forecast errors will benefit the system in terms of reduction in conventional generators production costs and renewable source curtailment (considered in [6]–[8]) as well as operation, maintenance and start up/shutdown costs of generators (considered in [7], [8]).

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While various factors such as renewable power penetration level, method of modelling (deterministic or stochastic methods as stated in [6]), scheduling time horizons and generation resources mix and their different ramp rate capabilities (as stated in [8]) affect the results of assessment and quantifying the value of forecasting, they all suggest significant amounts of stake, e.g. one case study in [6] shows that reduction in conventional generators cost for Ireland electricity market would be €1.2 M per year for every percentage decrease in forecast error of wind power generation. Work in [9] demonstrates that in addition to the economic value of renewable forecasting improvement, there would be improvement in reliability indexes as well.

Considering the value of renewable forecasting, there is an extensive research on different forecasting methods for wind power generation (reviewed in [10]–[12]), solar power generation (reviewed in [13]) or both of these sources (reviewed in [14], [15]).

These forecasting methods are generally classified based on forecasting time horizons i.e. short-term, medium-term, long-term and type of methods which include physical, statistical (time-series) and artificial intelligence techniques such as machine learning, fuzzy logic and hybrid methods. Articles [10], [12], [13], [15] provide a clear definition for forecasting time horizons (e.g. short-term is defined as 30 minutes to 6 hours a head in [12] or long-term is defined as 1 month to 1 year ahead in [13]). Articles [11], [12], [14], [15] categorise forecasting methods with respect to time horizons (e.g. physical approach suitable for long-term forecast as stated in [12] or artificial based methods for short-term forecast as mentioned in [11]). Article [14] also specifies spatial resolution in its classification.

The application area of each forecasting horizon in power systems (regardless of the method of forecasting) is covered in [10], [12]–[14] (e.g. day ahead forecast is considered for unit commitment in [13] or forecasts in the range of a few seconds has been suggested for voltage regulation and grid stability in [14]). It is worth mentioning that these definitions are not identical and vary from one reference to another.

In above mentioned methods, the input data to prediction models are mostly provided through one or limited sources of data and forecasting task is performed centrally by means of one single method or algorithm.

One promising approach that appears to be entirely absent from the literature on renewable energy forecasting is the use of prediction markets and this paper attempts to address this gap. Prediction markets are a form of financial markets where participants trade in contracts whose payoffs depends on unknown future events. In a truly efficient prediction market, at any time the market price will be the best predictor of the event [16]. Like in a stock market, participants in a prediction market can buy or sell contracts with prices associated with the probabilities for event possible outcomes [17]. As stated in [18]: *"There is mounting evidence that such markets can help to produce forecasts of event outcomes with a lower prediction error than conventional forecasting methods"*. It has been proved that they outperform over traditional approaches in various areas such as elections [19], sports matches [20], [21] and in business section for sales forecasting [22]. While they are widely celebrated amongst economists, they have not been deployed in power systems to date.

There has been a few examples in recent research works for using crowdsourced prediction methods in electricity sector, specifically for demand forecasting. Article [23] proposes an online platform where residential customers have access to their electricity consumption data provided by advanced metering infrastructures and can post questions and answers related to electricity consumption which would be used to achieve a prediction model. In article [24], a data collection platform through mobile devices has been proposed in which an electricity utility company can request for data and candidate workers can provide it.

The aforementioned crowdsourcing applications do not consider any specific kind of incentives or motivations for participants to provide accurate data. Regarding this issue, work in [25] provides an approach in which electricity supplier gives each consumer rewards proportional to their forecast accuracy. This way, consumers have incentives to forecast as accurately as possible or adjust their electricity consumption to match their own forecast. Work in [26] presents a design for a binary prediction market for electrical demand forecasting. All these proposals still are performed in a centralised format.

The remainder of this paper is organised as follows: Section II describes the methodology of the research. It provides background information about prediction markets and discusses how blockchain platforms implement these markets. Moreover, it delivers a conceptual framework for the application of prediction markets in renewable energy forecasting and hedging and demonstrates the financial gain that a typical wind power producer might attain by participating in these markets. Finally Section III concludes the paper.

II. Methodology

Prediction markets, in centralised forms, have existed for many years. In these type of markets, a trusted entity is in charge of running the market, recording the trades and specifying the outcome of the events. They finally perform market clearing tasks and distributes payoffs to the winners who speculated the outcome correctly. One of the best known platforms of such prediction markets is IEM (Iowa Electronic Markets) [27], developed by the faculty at the University of Iowa in 1988 as a research and teaching tool. It has been able to make efficient forecasts for various events such as political contests, with an average absolute error of about 2.5% for five presidential elections, as mentioned in [28] and also for forecasting box office receipts with a root mean square error not exceeding than 0.05, as examined in [28] for 11 movies predicted by a group of students. Another example of these prediction markets is Intrade, founded in 2001 in Ireland which correctly predicted US presidential elections outcome in 2008 [29] .

However, centralised prediction markets have their own limitations as they put restriction on global participation and on the types of markets that can be created or traded. Moreover, they require traders to trust the market operator who is resolving the market [30]. These challenges can be overcome through blockchain technology in an efficient manner.

A. Blockchain Prediction Markets

Blockchain is a trustless decentralised data ledger for storing transactions performed with cryptocurrencies, such as Bitcoin and Ethereum (ETH), as the medium of exchange. The validity of these transactions is confirmed through a decentralised consensus process among the users [31]. Therefore, this removes the role of intermediaries and since the data contained in each block can not be altered without being observed, its security and transparency is ensured.

In prediction markets, blockchain can be applied to record and verify transactions associated with trades happening in the market. Gnosis [32], Stox [33], Hivemind [34] and Augur [35] are examples of platforms for implementing blockchain hosted prediction markets. While a key challenge in prediction markets is the question of outcome determination [36], this issue matters in blockchain-hosted prediction markets as *oracle problem* which refers to providing real-word, off-chain data to blockchain. Game theoretical mechanisms [31] in recent announced blockchain platforms like Augur where independent participants can report, dispute and validate the data through a decentralised set of smart contracts, suggest a robust solution to this challenge.

In this paper the Augur platform [35] has been considered as the basis of prediction market design for renewable energy forecasting. Augur is a set of open source smart contracts that run on Ethereum blockchain. It allows cryptocurrency users to create prediction markets or trade contracts associated with possible outcomes of the events.

The next section is dedicated to explain how this protocol works based on Augur v1, with the use of information provided in references [30], [35], where further details can be found.

B. Augur Platform

The lifetime of a prediction market in Augur consists of four stages: creation, trading, reporting and settlement.

1) Market Creation: A prediction market can be created by anyone with a small cost according to the amount of gas used on Ethereum. A market creator in Augur sets an event end time, a resolution source to be used by reporters to determine the outcome of the event and a designated reporter to submit the first public report on the outcome, within three days after market end-time (which can be disputed by other reporters).

Moreover, the market creator should lock up some capital for two type of bonds: *validity bond* and *no show bond*. Normally, these bonds would be returned to market creators, but when the final outcome of the market is invalid, the validity bond would go to reporters in reporting fee pool, and in the case that the designated reporter does not return within three days after the market end-time to submit the first report, the no show bond would be given to the first public reporter.

To earn money, market creators can set a creator fee which will be collected by them whenever shares are settled.

2) Trading: Augur supports three types of prediction markets including binary market for events with yes/no outcomes, categorical markets for events with more than two but not more than eight possible outcomes and scalar markets with a wide range of potential outcomes between a lower and an upper band specified by the market creator.

Market participants forecast the outcomes of events by trading shares associated with those market outcomes. There is an order book for every market and orders created by participants are filled by an automated matching engine that exists within Augur's smart contracts.

3) Reporting: Final outcomes of the events are determined by Augur decentralised oracle mechanism. It consists of a process during which profit-motivated reporters report the actual final outcome of the event or dispute others' reports. Those reporters whose reports are consistent with consensus are financially rewarded (by paying them reporters' fee), while those reporters whose reports are not consistent with consensus will be at a loss. Each reporting and disputing round last seven days in Augur v1. Utilisation of game theoretical incentive mechanism [31] justify this reporting approach to reach consensus.

4) Settlement: When the final outcome of the event is specified by reporting process, market will be settled and payoffs will be distributed among shareholders. Since the value of a complete set of shares is equal to 1 ETH, the amount of payoffs, depending on the type of market, can be 0, 1 or a fraction of 1 ETH per share. Settlement fees (including creator's fee and reporters' fee) are deducted from share holders' payoffs.

C. Prediction Market Framework for Renewables

While prediction markets can have a broad range of applications in power systems, in this section we discuss this approach for renewable energy forecasting and hedging as two specific use cases.

1) Forecasting: Fig.1 presents a conceptual framework for implementing a prediction market to forecast different uncertainties associated with renewables. It should be mentioned that wind power plant has been selected as a typical renewable energy source and the idea can simply be generalised to other renewable sources such as solar power plants.

The market creator of the prediction market can be either a renewable energy producer or an electric network operator who may seek more accurate forecasting for different applications areas. Therefore, they should post appropriate questions in prediction markets respective to their application areas.

A renewable energy producer may wish to create a prediction market for participating and bidding in day ahead electricity market [5], maintenance scheduling [10], specifying potential areas for investment decisions [37] and making decisions when they want to buy weather derivatives [38] to hedge against poor weather conditions.

Electric network operators on the other side, may create prediction markets to make decisions related to planning and operation of the overall electric system such as unit commitment, economic dispatch, capacity reserve requirements and electricity market clearing [12].

As Fig.1 shows, renewable energy prediction markets in Augur platform, depending on the applications and respective questions, can be binary or scalar. For both types of markets, some examples of questions according to each application area have been provided in this figure.

As it is depicted in Fig.1, the meaning behind price per share and payoffs in a binary market would be different from scalar market in Augur.

In a binary market in Augur, participants speculate the answer (*Yes* or *No*) to the question related to the event with a probability assessed for it and then trade associated shares with a price according to probability. For example, price for buying a *Yes* share with 50 percent probability would be 0.5 ETH. After market finalisation, holders of the share associated with the correct answer are considered as winners and payoffs to them is 1 ETH per share (minus settlement fees).

However, in a scalar market, participants can trade two shares, *Long* share indicating an increase in the value of outcome and *Short* shares indicating a decrease in the value of outcome. Participants speculate on the outcome of the events somewhere between the lower and upper bands with its direction (an increase or decrease) and then trade either *Long* or *Short* shares. A complete set of shares in a scalar market amounts to 1 ETH, like binary markets, but payoffs to each share holder is a fraction of 1 ETH, which is defined linearly based on the final value of outcome and the distance of the share from the upper and lower bands.

Depending on whether the intention of market creators is to obtain final forecasting results or is just to assess potential wind speed in order to use it as an input data in their own developed prediction model, forecast variable can be either wind power or wind speed.

2) Hedging: While forecasting is the most widely used and best known application of prediction markets, another useful application would be hedging against undesired events, which is demonstrated in Fig.2. This can be achieved through buying the shares associated with the event which would negatively affect the buyer, as a form of insurance.

While future contracts and weather derivatives already exist in some exchanges or in bilateral forms and can be used as a hedging tool for renewable sources, as considered in [39] for wind power producers, since weather is not a storable and tradable good, making the standard futures pricing framework unusable [40], pricing weather derivatives requires forecasting on underlying weather variable [38]. In prediction markets, on the other hand, since the price of the shares are associated with the probability of the event, thus it is a direct result of forecasting and the issue of pricing derivatives would not be a problem any more. This is the advantage of hedging through prediction markets compared to bilateral forms of derivatives. In the field of renewable energy sources, wind power producers for example, who can lose money in poor wind speed conditions, can create a binary market in Augur and then buy shares indicating that wind speed will be lower than their initial forecasts. In this way, if this poor wind speed happens, they will earn money through their payoffs in prediction market and hence they would be hedged against poor weather conditions.

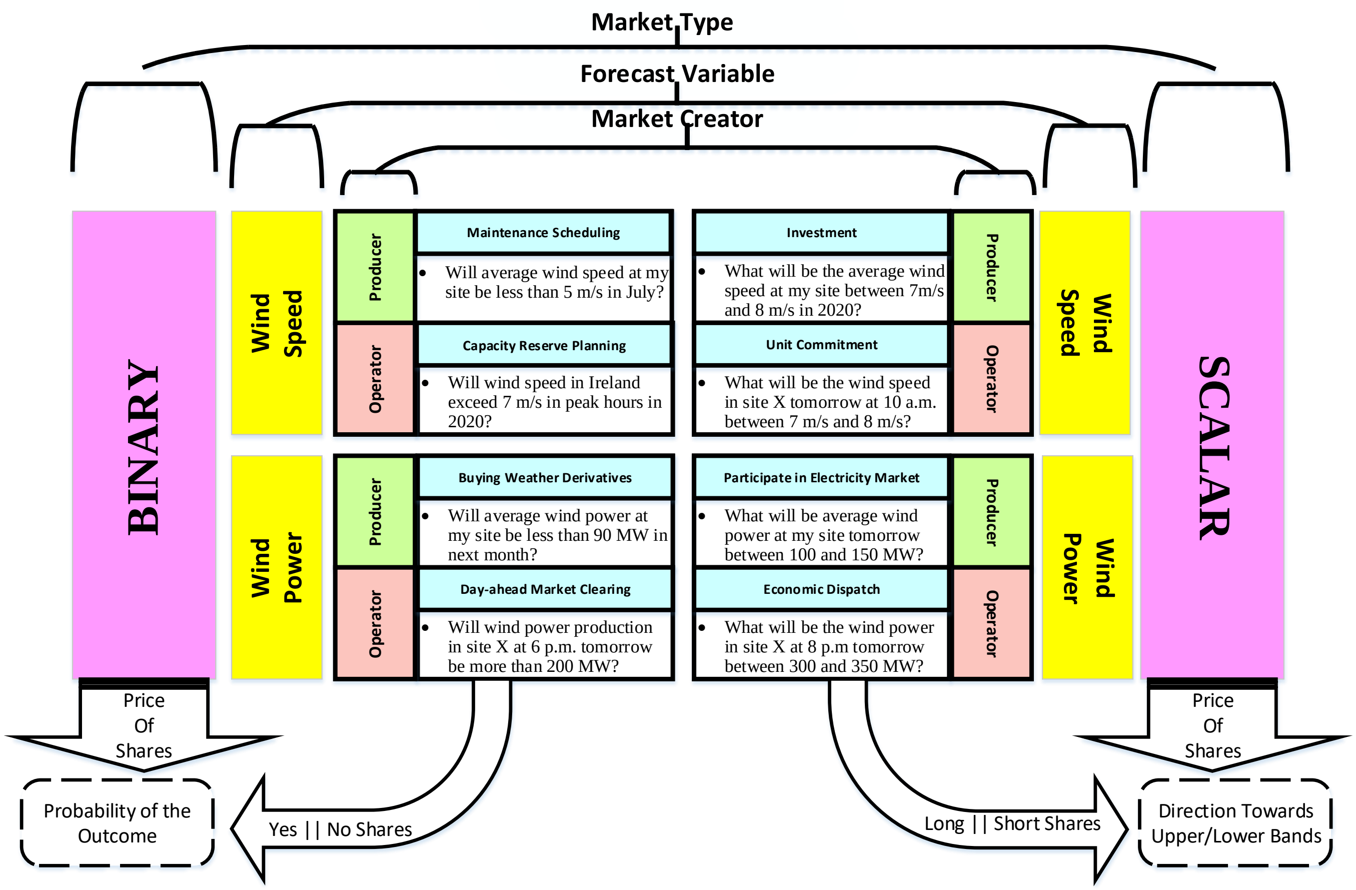

Fig. 1. Wind Energy Prediction Market in Augur.

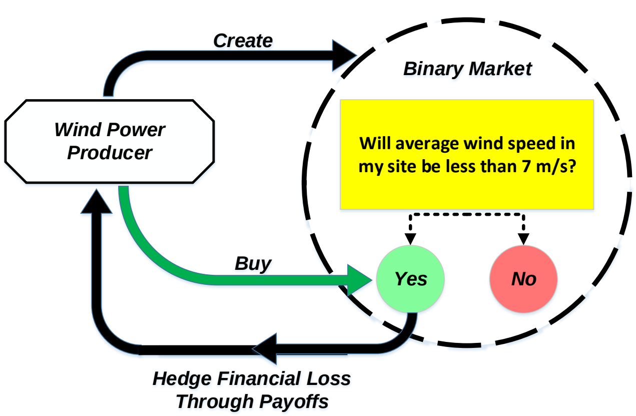

Fig. 2. Wind Power Hedging through Prediction Markets.

D. Case Study

In this section, we attempt to illustrate the financial flexibility of a typical wind power producer through hedging its monthly revenues by participating in a blockchain prediction market. The basic characteristic of the wind farm belonging to this producer is shown in Table I. By considering the fact that he aims to maintain his investment profitably, his expected revenues and consequent payback period is based on a wind speed of 8 m/s. Therefore, as an example, a wind speed of 7 m/s would affect his revenues as demonstrated in Table II. It should be noted that in all calculations, ETH has been considered equivalent to 146 Euro. It is worth mentioning that stablecoin cryptocurrencies, which their value is pegged to fiat money facilitate less fluctuations in price.

For investigating and evaluating the proposed hedging strategy for the wind power producer, We consider this binary prediction market in Augur platform: *Will the average wind speed at site XX be less than 7.5 m/s in May 2020?* Settlement fees for this market are set to 3% totally. The market trading phase is from 15th to 30th of April 2020. A sample order book for this prediction market on the first day of trading period is

TABLE I. Assumed Wind Power Producer Characteristics.

Wind Farm Capacity	2.5 MW
Expected Wind Speed	8 m/s
Capacity Factor @ 8 m/s	40%
Turbine Availability	98%
Expected Monthly Energy	729,120 kwh
Energy Selling Price	8 cent.euro/kwh
Expected Revenue	400 ETH

TABLE II. Wind Power characteristics in poor wind speed.

Wind Speed	7 m/s
Capacity Factor @ 7 m/s	38%
Monthly Energy	464,031 kwh
Monthly Revenue	254 ETH
Amount Required to be Hedged	146 ETH

shown in Table III. It is a collection of open orders including ask (sell) and bid (buy) orders of *YES* shares indicating their quantities (Qty) and prices (ETH). We consider that wind power producer estimates a probability of above 60% occurrence of a wind speed lower than 7.5 m/s and by taking into account a 3% fees, the price per share that he is willing to pay would be equal or lower than 0.582 ETH. Therefore at the beginning of the trading period, he fills ask orders with the prices lower than this limit. After one week, on date 22th of April, by approaching to the event, wind power producer realises that there is more chance and around 70% probability can be expected for a wind speed lower than 7.5 m/s in his site. Thus, he places buy orders for up to 191 shares with a price up to 0.68 ETH. Although as it is obvious from the order book on this day, available in Table IV, the market is not liquid enough to take the other side of all his orders and so it is only partially filled with 55 shares.

The cash flow of wind power producer by considering costs associated with participating in prediction markets (for buying shares and paying settlement fees) and revenues through selling electricity in energy market plus payoffs in prediction market has been shown in Fig.3 over the timeline of the market in Augur.

As can be inferred from this figure, the gain through this hedging approach is 95 ETH; the difference between net cashflow after the settlement of the market (349 ETH) and expected revenue from selling energy without hedging it in prediction market (254 ETH). While this hedging tool did not completely cover the amount required to be hedged (146 ETH) due to lack of enough liquidity in the market, it succeeded to cover 65% of this amount which is a significant gain for wind power producer. However, this assumes counterparties were available.

It should be noted that since we aimed to show the effect of hedging through prediction market, revenues from selling electricity in periods other than hedging period (May 2020) have not been shown in Fig.3 as they are irrelevant to the subject. It is also worth mentioning that this timeline is based on Augur v1 platform. In Augur v2 [41] trading currency could be Dai (a cryptocurrency-backed stable coin) and the duration of designated reporting phase and first reporting window which are 3 days and 7 days, respectively, in version 1, will be reduced to 24 hours to resolve the market quicker.

TABLE III. Sample augur order book on 15 April 2020.

Ask Qty	Price (ETH)
78	0.7
12	0.68
97	0.59
101	0.58
94	0.56
40	0.54
93	0.52
Bid Qty	**Price (ETH)**

TABLE IV. Sample augur order book on 22 April 2020.

Ask Qty	Price (ETH)
9	0.74
11	0.73
23	0.71
77	0.7
55	0.68
191	0.68
15.5	0.65
Bid Qty	**Price (ETH)**

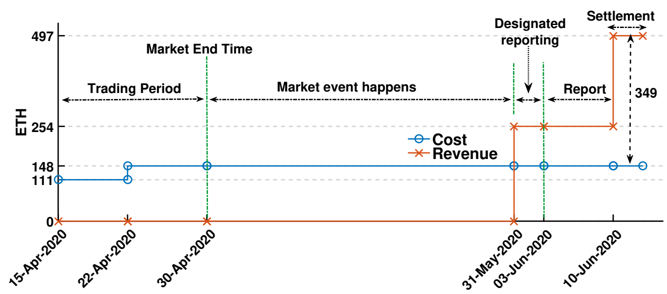

Fig. 3. Wind power producer cash flow during prediction market timeline.

III. Conclusion

A blockchain prediction market for renewable energy sources forecasting creates an environment where unlimited number of participants can compete with their predictions in the market and earn money for correct results in a decentralised way. Therefore, they have enough motivations in the form of monetary incentives to provide accurate information and develop the most efficient prediction models to achieve precise forecast results. Therefore, a renewable energy producer or the electric network operator can use the result of these markets for different purposes. In addition, buying shares associated with poor condition of underlying weather variable in a prediction market can be considered as a hedging tool for renewable energy producer as payoffs in winning situation will compensate the financial loss for these producers. The flexibility and decentralised nature of blockchain prediction markets make them a powerful forecasting tool for renewables. However, the success of this approach rely on the adequacy of liquidity. Further works will explore appropriate market mechanisms to enhance liquidity in prediction markets.

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