Prediction Markets as a Data Aggregation Mechanism

IEEE SmartGridComm, October 27th 2022

Dr. Paul Cuffe & Ms. Mahdieh Shamsi
University College Dublin, Ireland

This research has been funded by the Sustainable Energy Authority of Ireland under the SEAI Research, Development & Demonstration Funding Programme 2018, grant number 18/RDD/373, and additional funding provided by the UCD Energy Institute.

Prediction Markets

- Participants bet on the outcome of **future events** and trade contracts whose **payoffs** depend on the **true outcome** of the event

- Will candidate A be elected as president?

  Binary : Yes / No : Winner-takes-all

- **1 $ per share** for correct answers and **nothing to others**

- **Market price** represents the **probability** of the outcome

Decentralised Forecasting Methods in Energy Sector

Crowdsourcing methods to gather data from various sources

What is the **motivation** to provide accurate data?

In **prediction markets:** tangible **monetary incentives** for participants

Prediction Markets for Probabilistic Forecasting of Renewable Energy Sources

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

***Abstract*—This paper demonstrates how a binary prediction market is capable of achieving a probabilistic renewable energy forecast. In prediction markets, participants trade shares associated with the outcome of unknown future events (here, the renewable production, as a random variable), and the instantaneous price of shares represents the probability of the outcome. The focus of this study is to exploit this informational value of the prediction market price in renewable energy forecasting. To this end, in this paper three different methods of renewable probabilistic forecasting have been considered as the trading agents in a binary prediction market, the aggregated probability of the renewable output is elicited from the equilibrium price in this market and finally, the full cumulative distribution function of possible renewable output is extracted through regression analysis. The proposed method is applied to the test cases of three onshore wind farms in Australia. The simulation results suggest that the performance of the proposed method is superior to the individual models and forecasting is improved in**

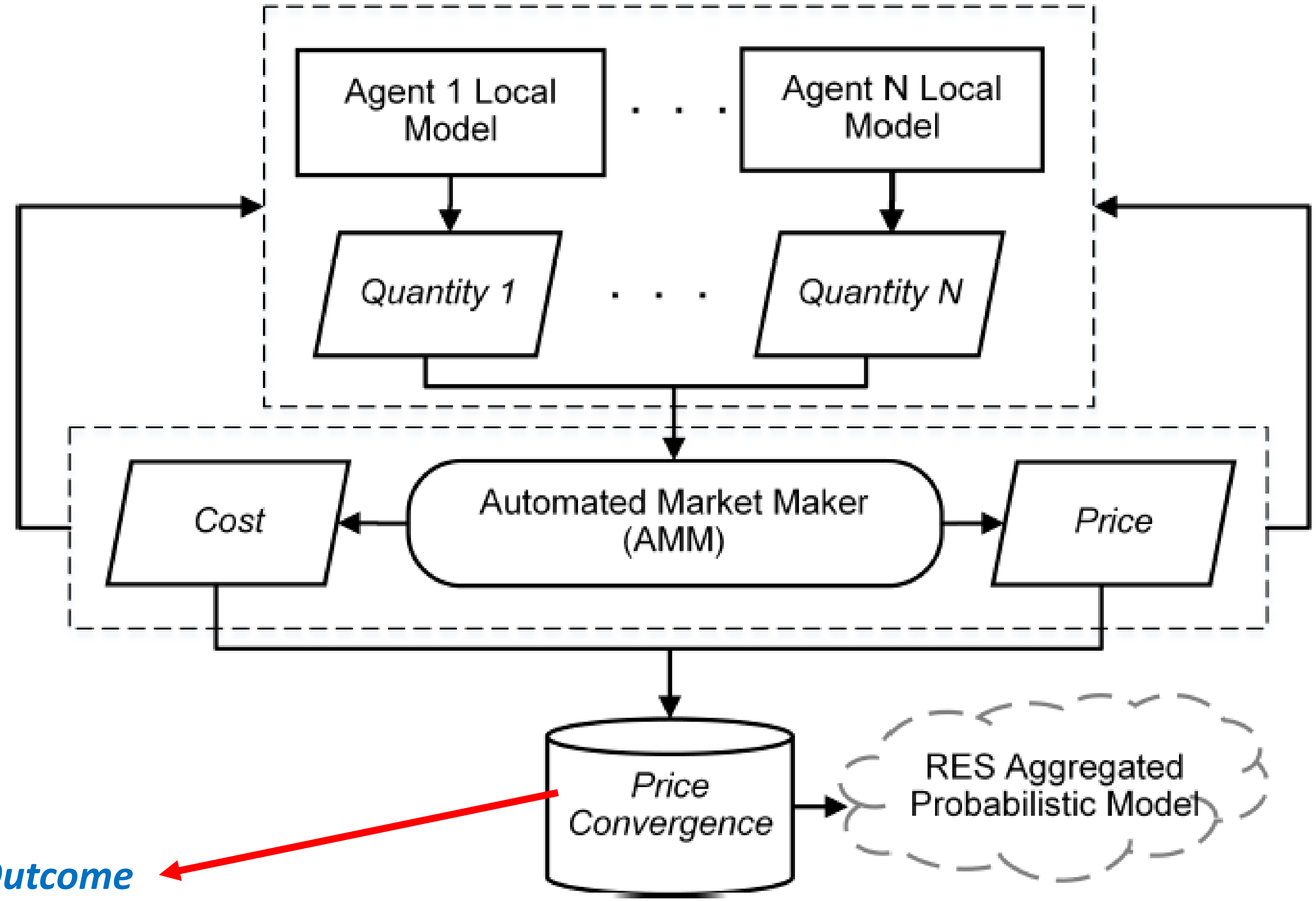
Decision making problems, mentioned above, can be improved by taking into account the uncertainty information of the point forecasts through probabilistic forecasting. Extensive research exists on this topic in the literature, for a detailed classification and review, we refer to [8], [9] and [10]. Here, within the scope of this paper, it suffices to note that these methods can be categorised into two groups: parametric methods assume a pre-defined shape for the distribution of forecast errors, such as Gaussian or beta ([11] and [12]) and estimate the relevant parameters, while nonparametric methods obtain empirical probability distributions from the historical data ([13] and [14]) without any prior assumption on the shape of errors distribution.

The above mentioned forecasting methods can be improved

I. INTRODUCTION

RENEWABLE energy is typically forecast by deterministic methods which provide a single value for the future production, referred to as point forecasts [1]. However, the results of these methods are unavoidably uncertain due to the volatility of these weather-based sources. The uncertainty associated with renewable energy forecasting poses technical and economical challenges to the operation and management of power systems [2]. At the system operator level, the tasks such as reserve requirement determination [3], unit commitment, and economic dispatch [4] will be affected by the forecast accuracy. From the perspective of Renewable Energy Sources (RES), this issue affects their trading strategies in electricity markets and

Probabilistic Forecasting of the Renewables' Output



Probability of the Outcome

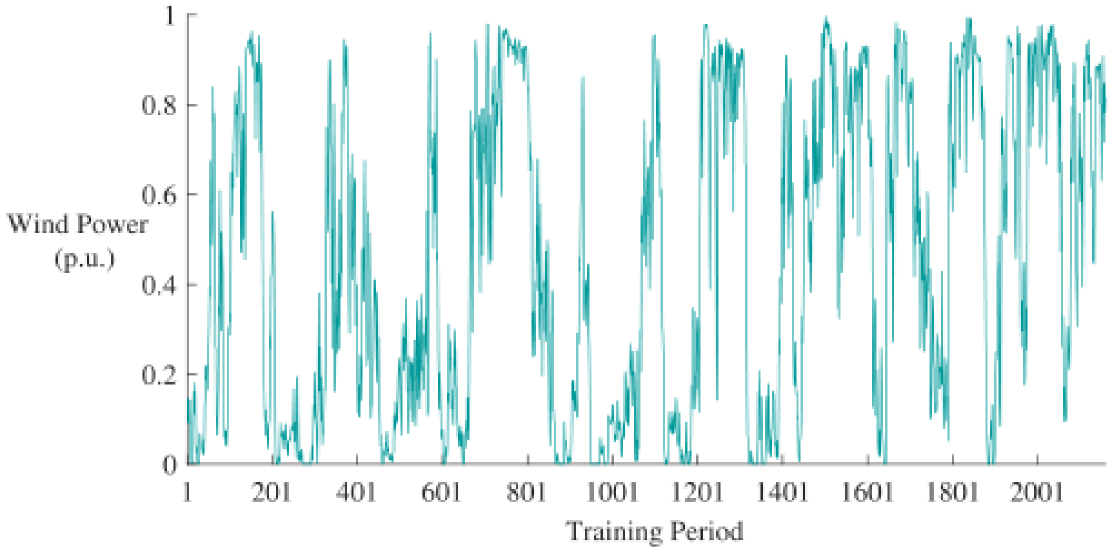
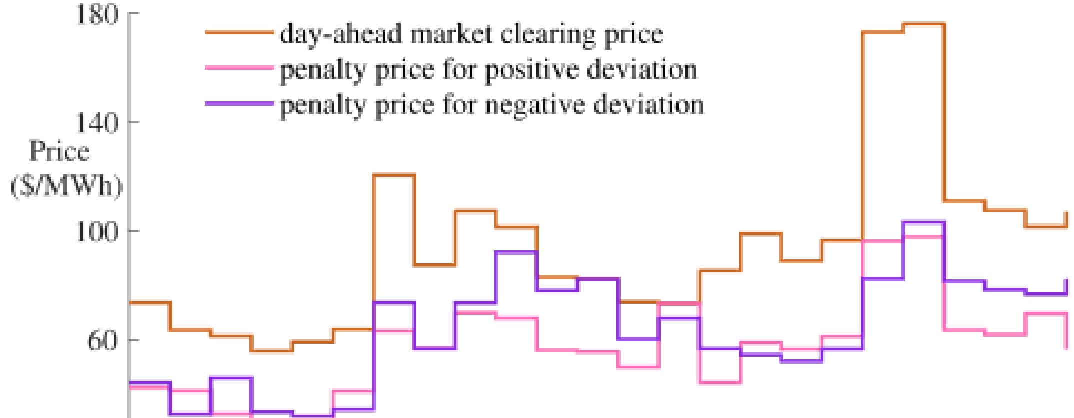


Fig. 2. Three months historical data (before 16-08-2018) of hourly power generation of Taralga wind farm used to train agents' forecasting models.



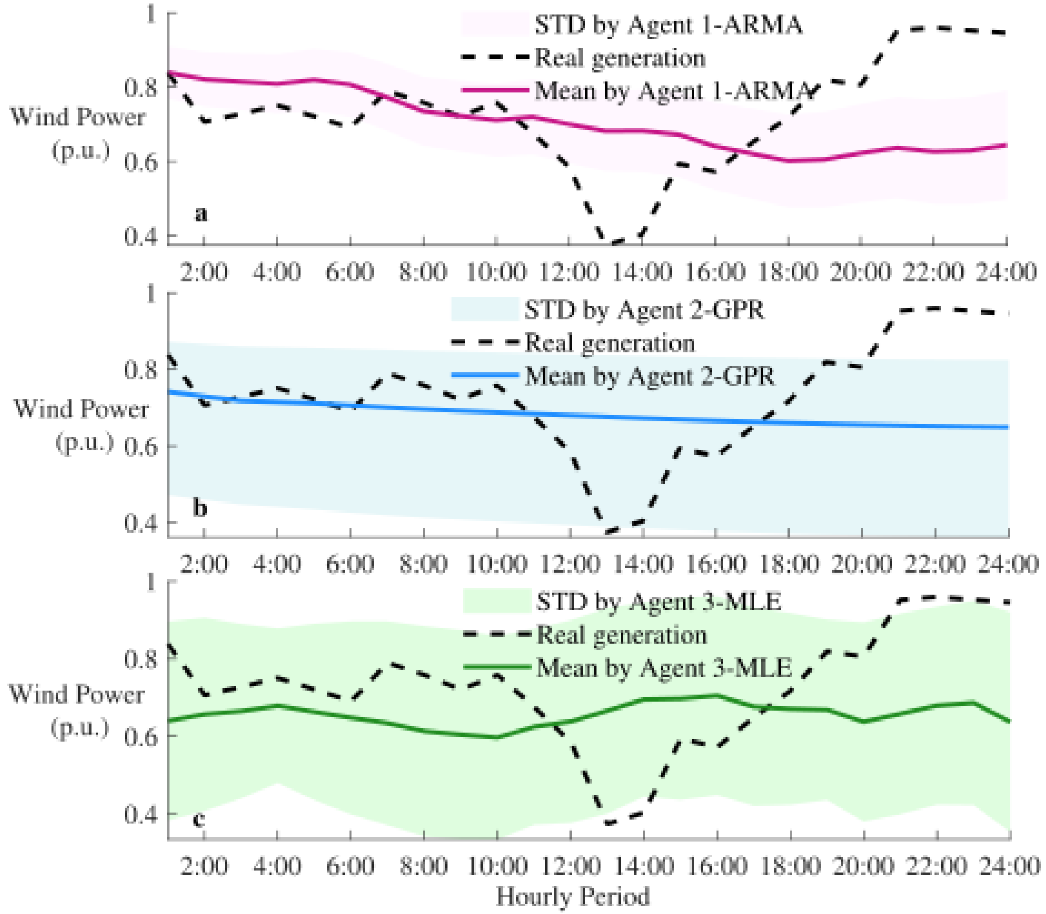
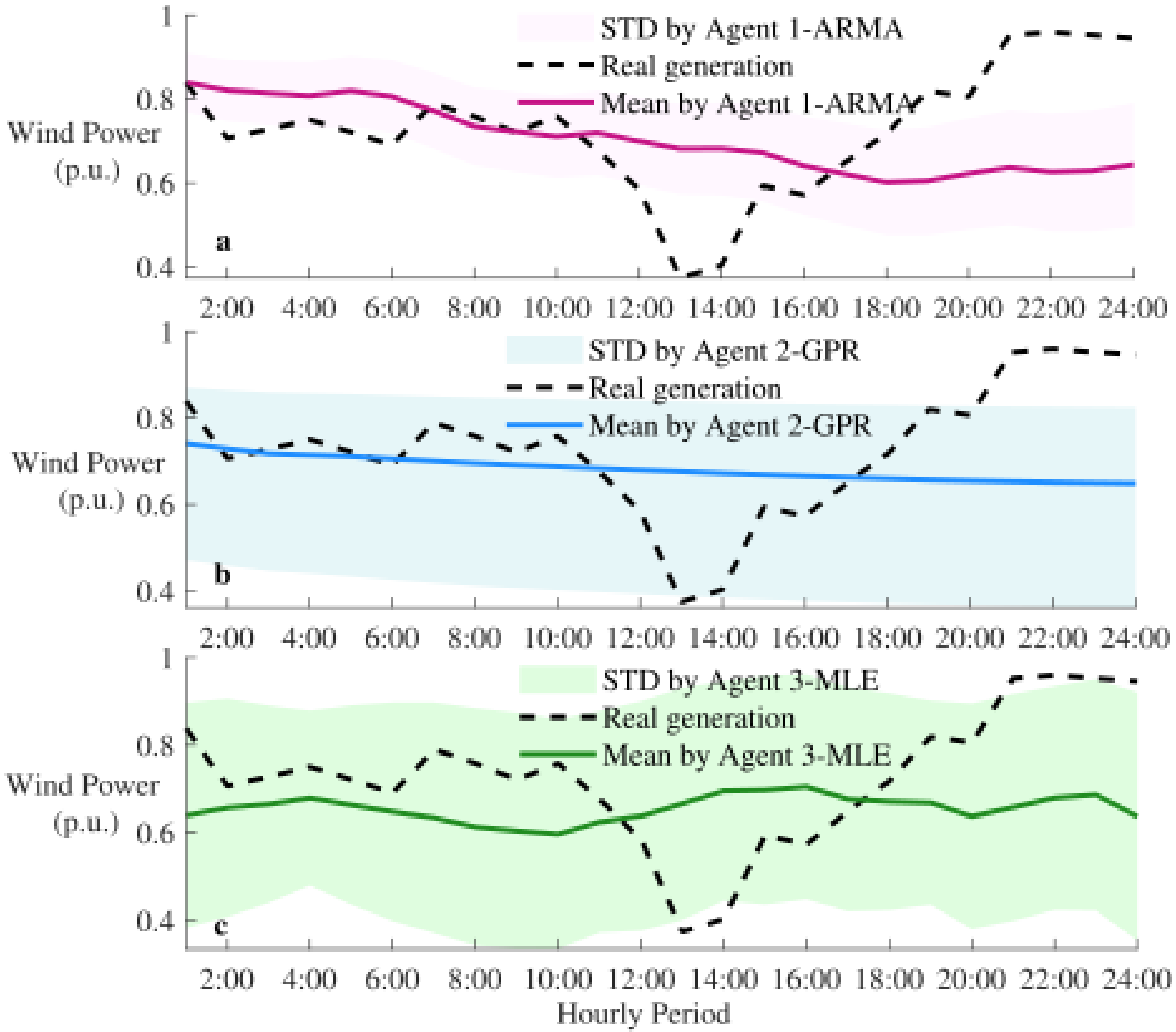
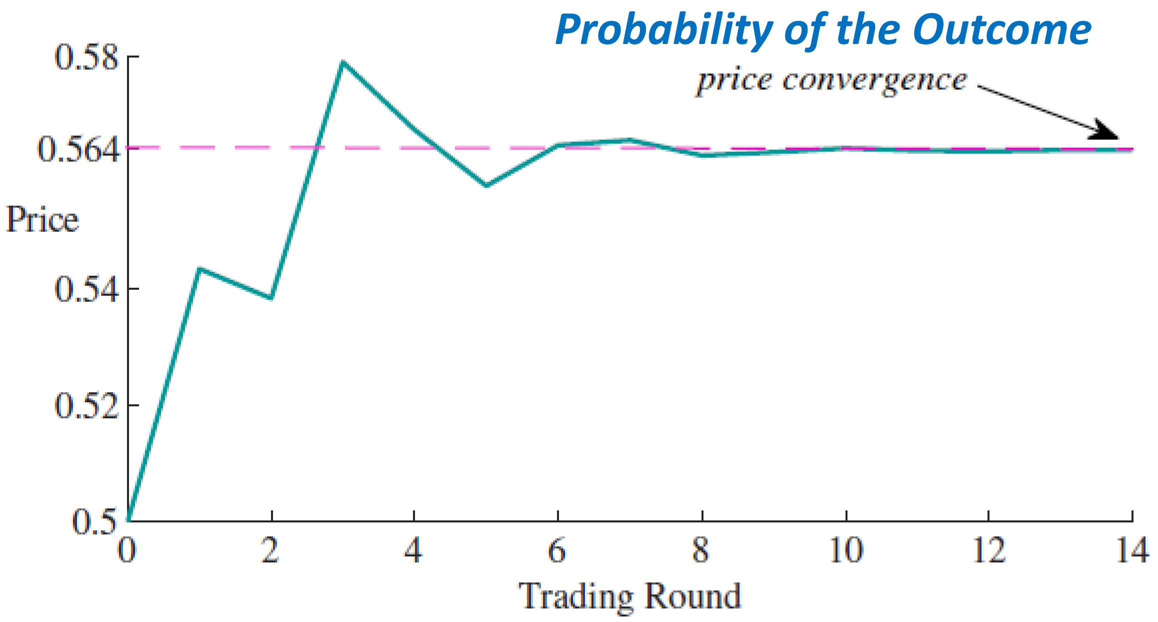


Fig. 4. Agents' individual predictions versus real power generation of Taralga wind farm on 16-08- 2018: a) Predicted by agent 1 based on ARMA model, b) Predicted by agent 2 based on GPR model and c) Predicted by agent 3 based on MLE model.



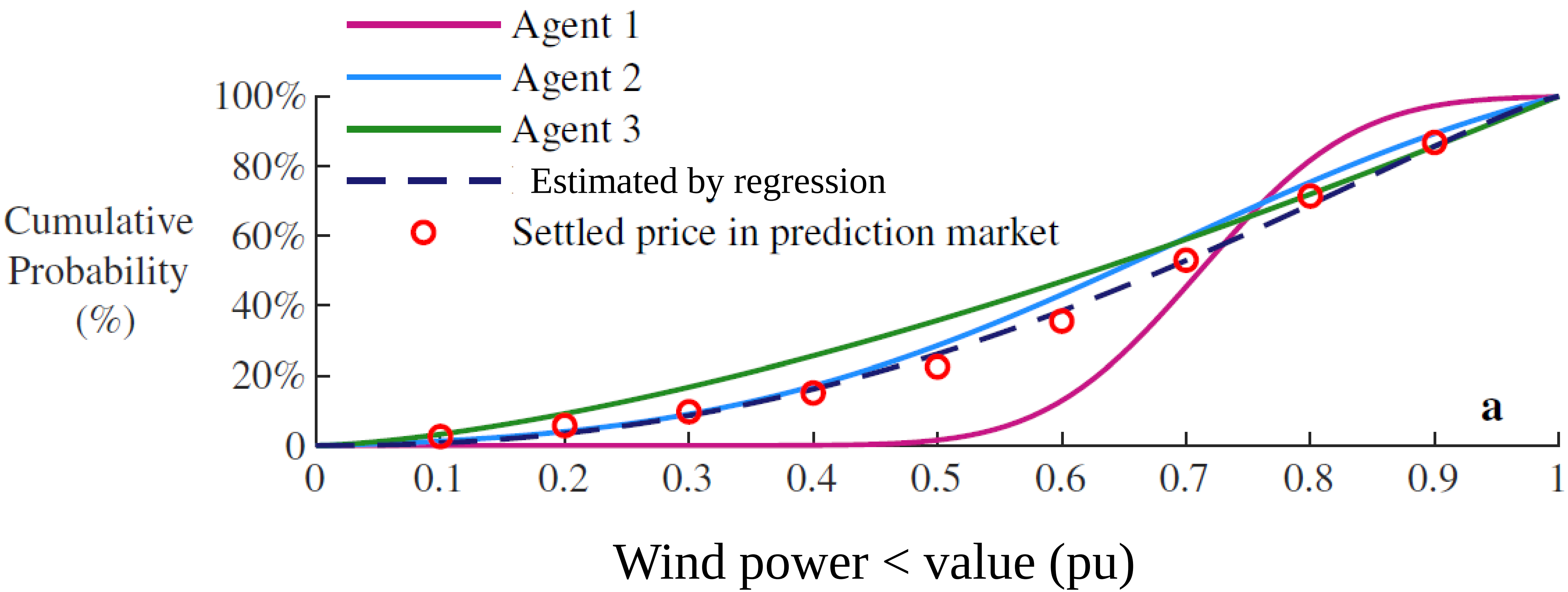
STD by Agent 1-ARMA
Real generation
Mean by Agent 1-ARMA
Wind Power (p.u.)
a
STD by Agent 2-GPR
Real generation
Mean by Agent 2-GPR
b
STD by Agent 3-MLE
Real generation
Mean by Agent 3-MLE
c
1
0.8
0.6
0.4
2:00
4:00
6:00
8:00
10:00
12:00
14:00
16:00
18:00
20:00
22:00
24:00
Hourly Period

Sample of a binary market simulation



Will the renewable generation be less than a certain MW amount?

Extracting the Full Predictive Density Function



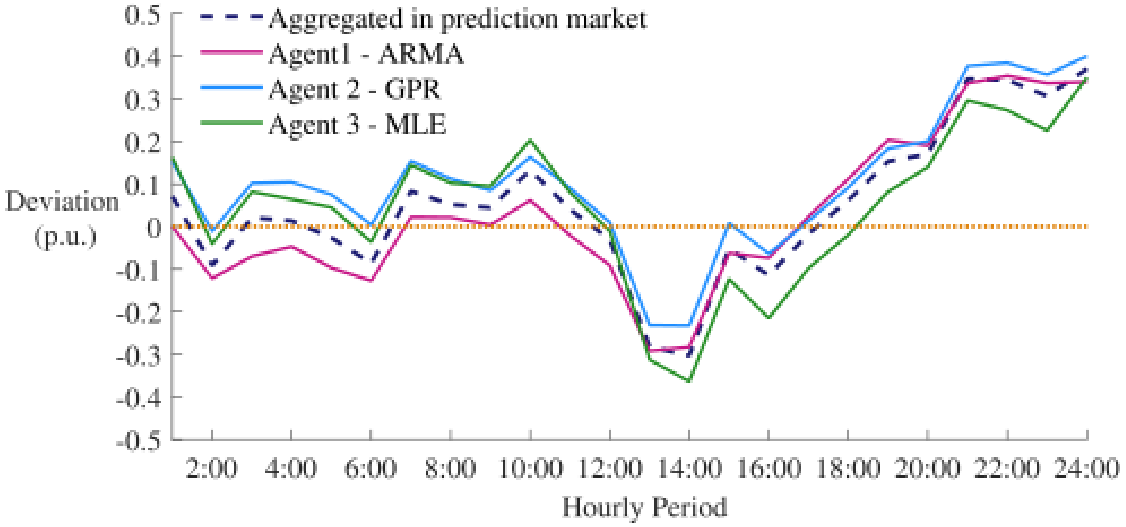


Fig. 9. Deviations of real power generation of Taralga wind farm from submitted day-ahead bids in each forecasting model on 16-08-2018.

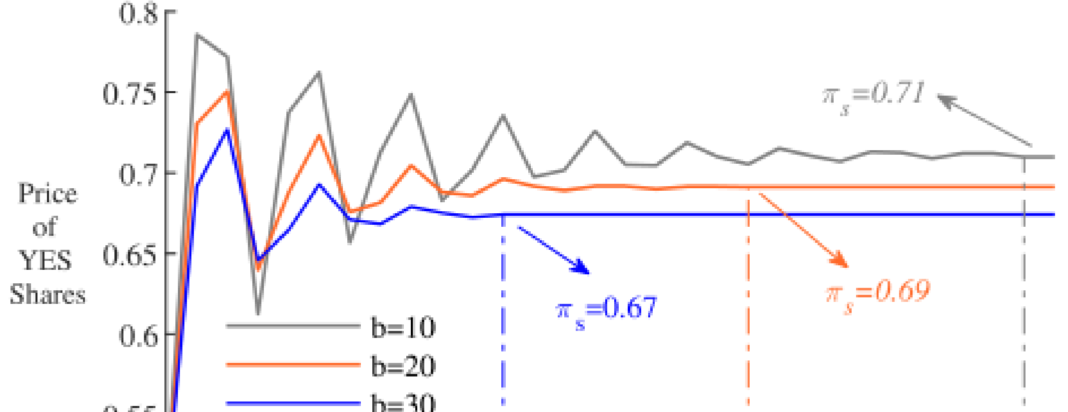


TABLE II

EVALUATION OF THE DIFFERENT METHODS PERFORMANCES IN THE FORECASTING OF BALD HILLS WIND FARM HOURLY GENERATION DURING LAST NINE MONTHS OF THE YEAR 2018

Forecasting Method	**RMSE**	**Imbalance costs**
Prediction Market (PM)	31.81 %	k$ 10, 686
Ensemble Mean (EM)	31.83 %	k$ 10, 846
Agent No. 1 with ARMA model	33.50 %	k$ 11, 170
Agent No. 3 with MLE model	33.83 %	k$ 11, 178
Agent No. 2 with GPR model	32.95 %	k$ 11, 792
Combined Weighted (CW)	33.66 %	k$ 13, 282

TABLE III

EVALUATION OF THE DIFFERENT METHODS PERFORMANCES IN THE FORECASTING OF WOOLNORTH WIND FARM HOURLY GENERATION DURING LAST NINE MONTHS OF THE YEAR 2018

Forecasting Method	**RMSE**	**Imbalance costs**
Prediction Market (PM)	31.37 %	k$ 10, 831
Ensemble Mean (EM)	31.33 %	k$ 10, 934
Agent No. 2 with GPR model	31.45 %	k$ 11, 358
Agent No. 3 with MLE model	32.18 %	k$ 11, 426
Agent No. 1 with ARMA model	34.73 %	k$ 11, 521
Combined Weighted (CW)	32.11 %	k$ 15, 453

TABLE II

EVALUATION OF THE DIFFERENT METHODS PERFORMANCES IN THE FORECASTING OF BALD HILLS WIND FARM HOURLY GENERATION DURING LAST NINE MONTHS OF THE YEAR 2018

Forecasting Method	**RMSE**	**Imbalance costs**
Prediction Market (PM)	31.81 %	k$ 10, 686
Ensemble Mean (EM)	31.83 %	k$ 10, 846
Agent No. 1 with ARMA model	33.50 %	k$ 11, 170
Agent No. 3 with MLE model	33.83 %	k$ 11, 178
Agent No. 2 with GPR model	32.95 %	k$ 11, 792
Combined Weighted (CW)	33.66 %	k$ 13, 282

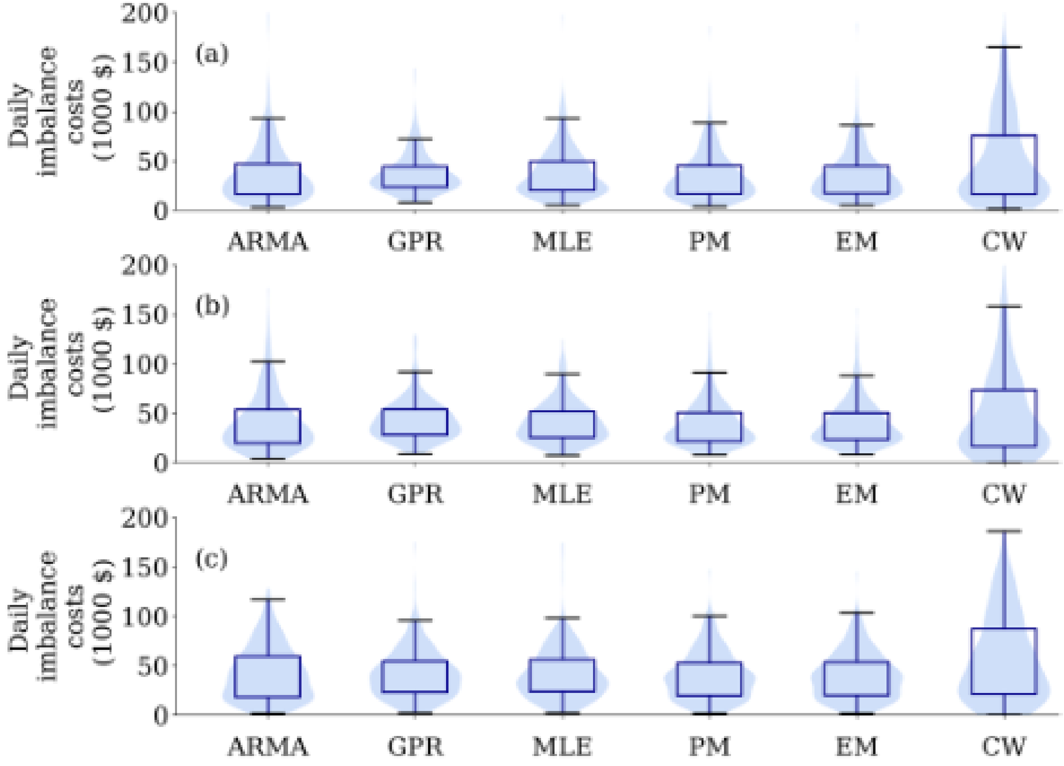


Fig. 12. Box and whisker, together with Violin plot of the probability of the violation of system constraints versus actual values of the system constraints. The boxes cover 50% of the data points in each range, while the whiskers include 49.3% of the data points (the remainders are considered as outliers). The sides of the violins in Violin plot represent the probability density of the data in each range, smoothed by a kernel density estimator. (a) Taralga wind farm; (b) Bald Hills wind farm; (c) Woolnorth wind farm.

References

[1] A. Costa, A. Crespo, J. Navarro, G. Lizcano, H. Madsen, and E. Feitosa, "A review on the young history of the wind power short-term prediction," *Renew. Sustain. Energy Rev.*, vol. 12, no. 6, pp. 1725–1744, 2008.

[2] J. Yan, F. Li, Y. Liu, and C. Gu, "Novel cost model for balancing wind power forecasting uncertainty," *IEEE Trans. Energy Convers.*, vol. 32, no. 1, pp. 318–329, Mar. 2017.

[3] M. A. Matos and R. J. Bessa, "Setting the operating reserve using probabilistic wind power forecasts," *IEEE Trans. Power Syst.*, vol. 26, no. 2, pp. 594–603, May 2011.

[4] A. Botterud *et al.*, "Demand dispatch and probabilistic wind power forecasting in unit commitment and economic dispatch: A case study of illinois," *IEEE Trans. Sustain. Energy*, vol. 4, no. 1, pp. 250–261, Jan. 2013.

[5] A. Fabbri, T. G. S. Roman, J. R. Abbad, and V. H. M. Quezada, "Assessment of the cost associated with wind generation prediction errors in a liberalized electricity market," *IEEE Trans. Power Syst.*, vol. 20, no. 3, pp. 1440–1446, Aug. 2005.

[6] J. Browell, "Risk constrained trading strategies for stochastic generation with a single-price balancing market," *Energies*, vol. 11, no. 6, 2018, Art. no. 1345, doi: 10.3390/en11061345.

[7] B. Kraas, M. Schroedter-Homscheidt, and R. Madlener, "Economic merits of a state-of-the-art concentrating solar power forecasting system for participation in the spanish electricity market," *Sol. Energy*, vol. 93, pp. 244–255, 2013.

[8] R. J. Bessa *et al.*, "Towards improved understanding of the applicability of uncertainty forecasts in the electric power industry," *Energies*, vol. 10, no. 9, 2017, Art. no. 1402, doi: 10.3390/en10091402.

IV. Conclusion

Prediction markets use the wisdom of the crowd principle to aggregate information and provide accurate forecasts of unknown future events. In a binary prediction market, the settled price represents the crowd consensus on the probability of the outcome. The production of a renewable energy source is a random variable for which its probabilistic forecasting can be obtained through such a market. While utilising prediction markets for some applications may face some legal risks, the focus of this paper is on the capability of these predictive tools to bring together collective expertise. This paper demonstrated how a prediction market has the potential to aggregate the results of agents' local RES forecasting models and produce the full cumulative distribution function.

The results of applying the method to three real wind farms suggest that the quality of forecasting and the consequent bidding strategy in the day-ahead electricity market will be improved by the proposed method in comparison with the agents' individual models leading to a reduction in imbalance costs. The scale of such improvement is expected to be increased

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

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

***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**

$F_P(p)$ 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 ($)

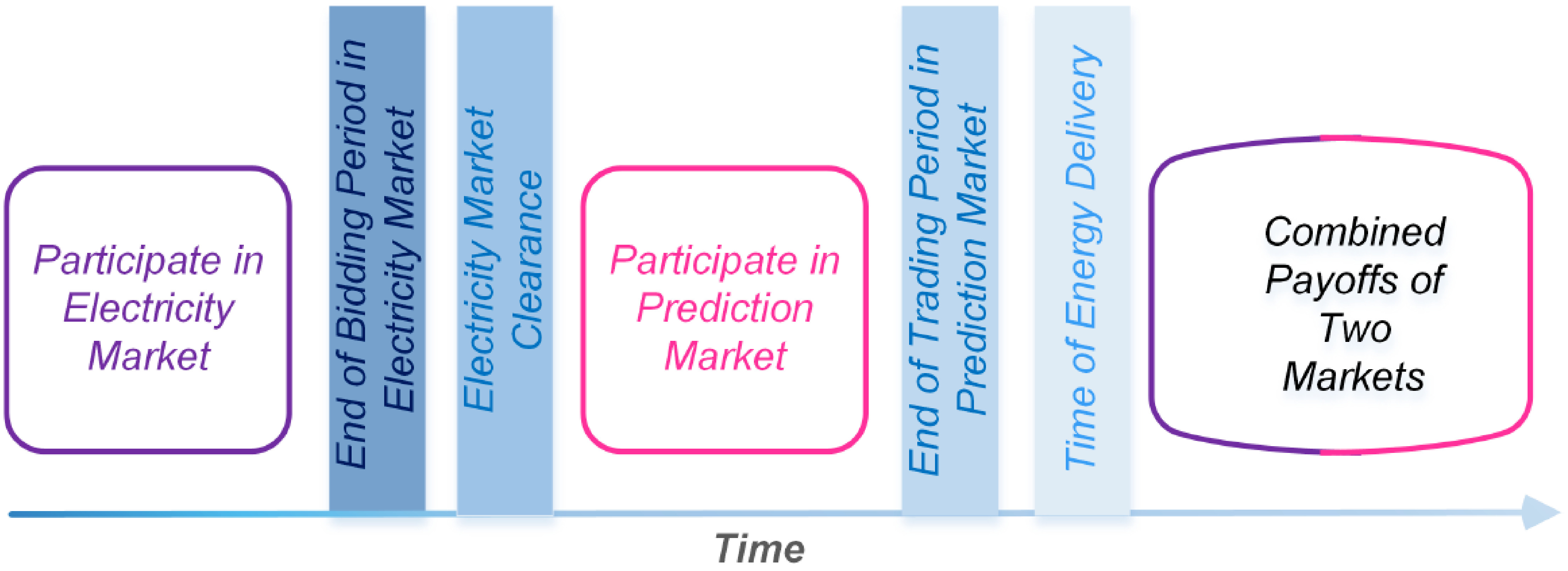
j revenue of the wind power producer ($)

k settlement fees in the prediction market (%)

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.

Hedging the Renewables' Revenue in the Day-ahead Electricity Market

Taking opposite positions in the two markets:



Electricity Market

- **Day-ahead** electricity market, **balancing market**
- **Deviation** between submitted bids and actual generation: **Imbalance Costs**
- Resource volatility of **renewables**
- Financial Risk to be **hedged**

Imbalance cost (deviation loss)

Dual Settlement mechanism

$$L_e(p) = \begin{cases} P_{max}\, q\,(p - c^*) & p \leq c^* \\ P_{max}\, \lambda\,(p - c^*) & p \geq c^* \end{cases}$$

Underproduction

Overproduction

Imbalance prices (q, λ)

Actual generation of renewable (stochastic variable) (p)

Day - ahead Bid (c^*)

Scalar Prediction Market

Short shares payoff

$$H(x) = \begin{cases} 1-k & x \le x_1; \\ (x_2 - x)(1-k)/(x_2 - x_1) & x_1 \le x \le x_2; \\ 0 & x \ge x_2. \end{cases}$$

Long shares payoff

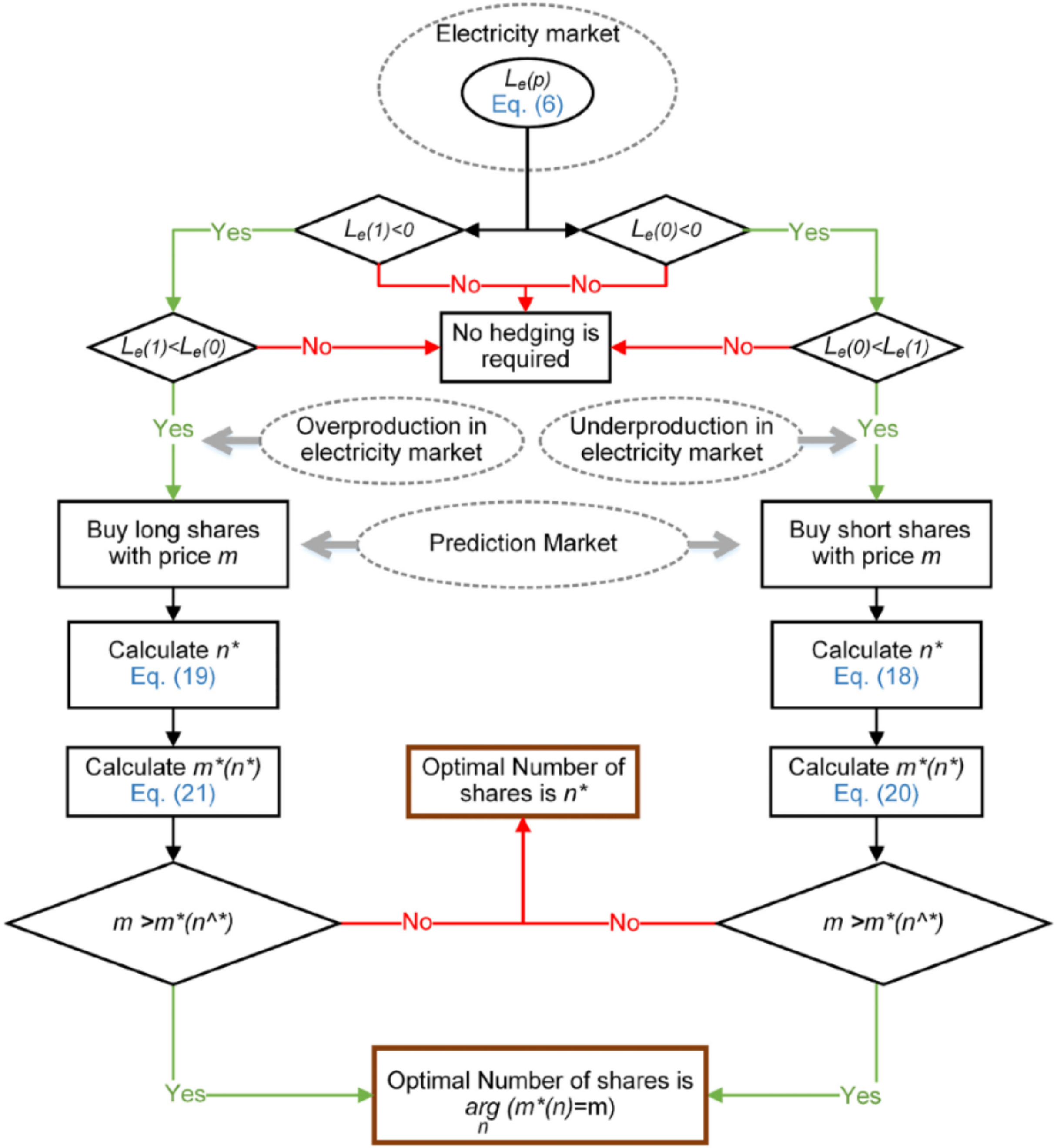
$$G(x) = \begin{cases} 0 & x \le x_1; \\ (x - x_1)(1-k)/(x_2 - x_1) & x_1 \le x \le x_2; \\ 1-k & x \ge x_2. \end{cases}$$

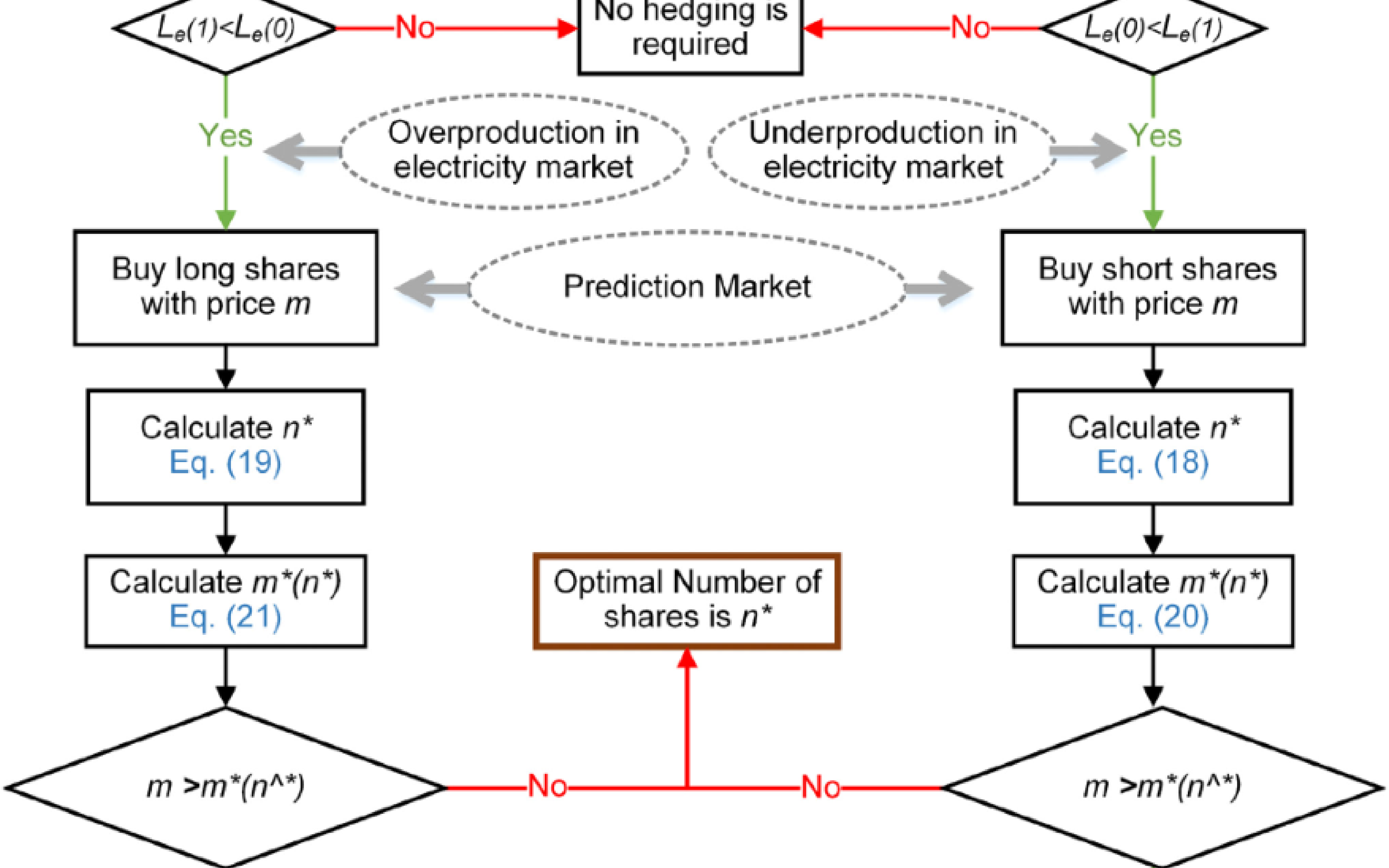
Actual value of the variable
Here: p (renewable generation)

Upper band

Lower band

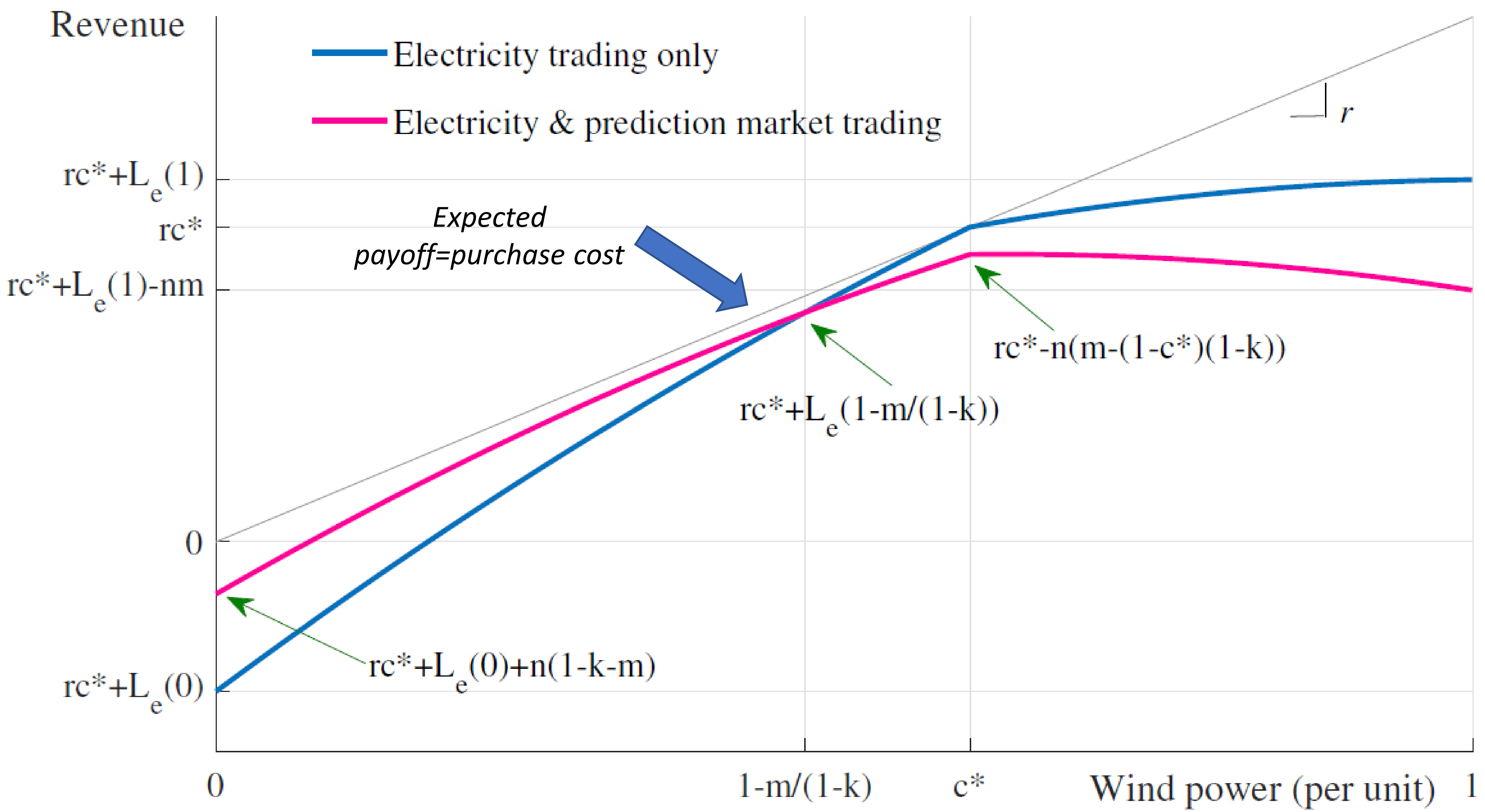
Proposed Hedging Strategy:





$L_e(1)<L_e(0)$
No
No hedging is required
No
$L_e(0)<L_e(1)$
Yes
Overproduction in electricity market
Underproduction in electricity market
Yes
Buy long shares with price *m*
Prediction Market
Buy short shares with price *m*
Calculate n^* Eq. (19)
Calculate n^* Eq. (18)
Calculate $m^*(n^*)$ Eq. (21)
Optimal Number of shares is n^*
Calculate $m^*(n^*)$ Eq. (20)
$m > m^*(n^*)$
No
No
$m > m^*(n^*)$

Combining revenues of the two markets



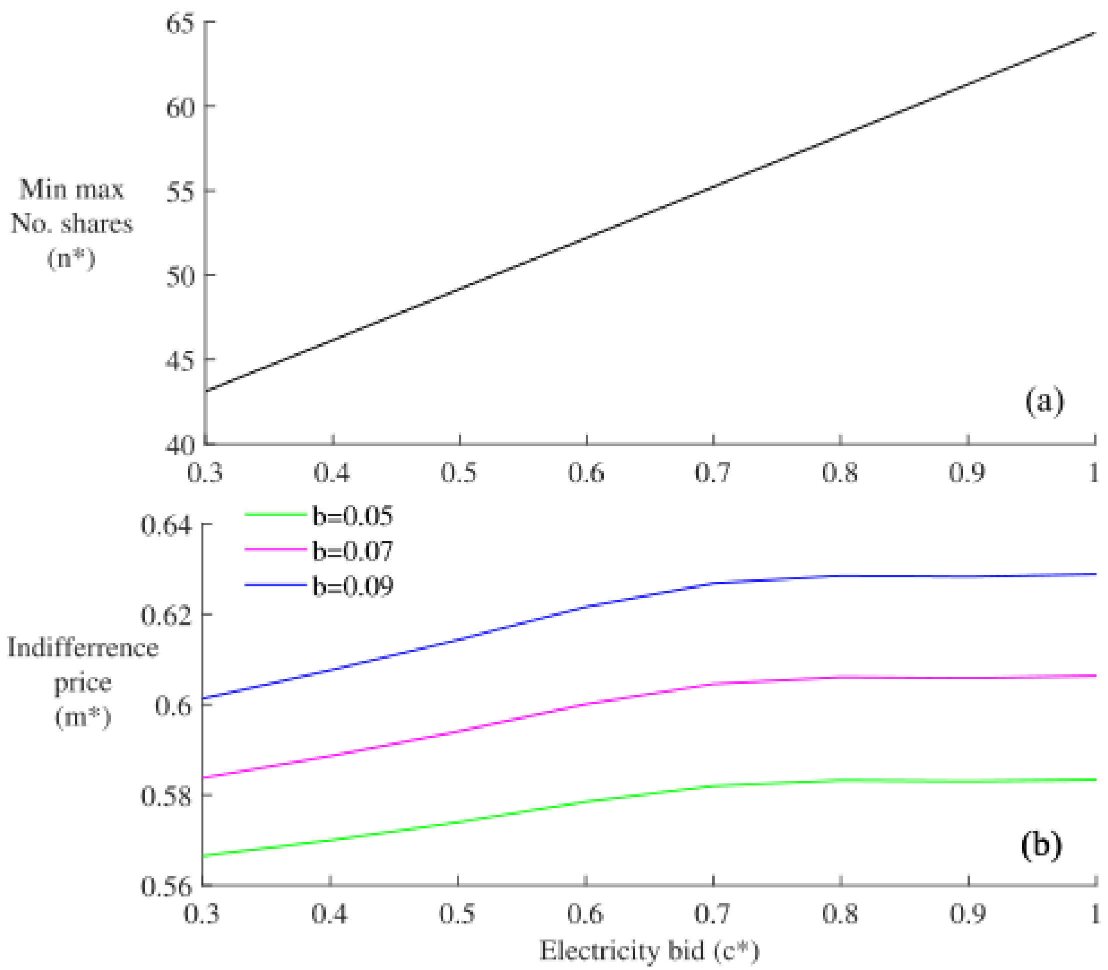


Fig. 8. Effect of electrical bid and risk-adversity on the prediction market trading strategies a) number of shares in min max strategy b) price in utility indifference strategy.

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

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.

Conclusion

Prediction markets benefit:

- Renewable energy **producers**
- Power system **operators**

By:

- Providing an **accurate forecasting signal**
- **Hedging revenue** against imbalance costs in electricity market

Thank you

Questions?

paul.cuffe@ucd.ie or mahdieh.shamsi@ucdconnect.ie