

Analytical Model of Day-ahead and Real-time Price Correlation in Strategic Wind Power Offering

Xin Fang and Mingjian Cui

Abstract—In this paper, the model of strategic wind power offering in the day-ahead (DA) market is proposed considering the uncertainties of wind power production, and price forecasting of DA and real-time (RT) market. The wind power deviation in the RT market is settled with the two-price mechanism based on the deviation direction and the relation between the locational marginal prices (LMPs) of DA and RT. Instead of using the point forecasting for the DA and RT LMPs, the uncertainties of LMP forecasting are modeled. In addition, the correlation between the forecasting errors of DA and RT LMP are directly modeled instead of generating the correlated scenarios. Finally, the optimal offered quantity of wind power in the DA market is derived using the probability theory based on the probabilistic wind power forecasting. The case study using the price data of actual DA and RT from Midcontinent Independent System Operator (MISO) validates the effectiveness of the proposed model. It shows that the correlation of the forecasting errors of DA and RT LMP has a significant impact on the wind power quantity offered by DA and revenue results.

Index Terms—Electricity market, wind power, uncertainty, correlation, strategic wind power offering.

I. INTRODUCTION

WIND power is substantially increasing in power systems because of the environment policies and reducing capital cost for wind technology [1]. In the United States, most of the wind power plants are connected in the deregulated electricity markets such as Midcontinent Independent System Operator (MISO) and Electric Reliability Council of Texas (ERCOT) [2]–[4]. One important issue of wind power producers in these deregulated electricity markets is to maximize its revenue [5]. Most of the electricity markets in the United States are organized with a day-ahead (DA) forward market and a real-time (RT) deviation settlement market which settles the deviations between the actual demand and the DA forecasted amount. A two-price mechanism is used by several European electricity markets to settle the wind power deviations between the DA and RT mar-

kets to reduce the stochastic arbitrage potential for wind power producers. More details about the two-price mechanism can be found in [6].

In the market operation, the wind power producers utilize the probabilistic wind power forecasting shown in Fig. 1 to reduce its financial loss [7] due to the wind power volatility. The percentage value on the right side of Fig. 1 is the probabilistic quantile value in the probabilistic forecasting. In addition, during the DA market offering, not only the actual wind power production is uncertain, but the DA locational marginal prices (LMPs) and the RT LMPs are also uncertain. The DA LMPs are hourly prices and RT LMPs in most of International Standardization Organizations (ISOs) in the United States are 5-minute prices. The joint probability distribution function of the DA and RT forecasted LMPs is depicted in Fig. 2. Therefore, in wind power DA offering method, both the wind production and the price uncertainties from DA and RT markets should be considered.

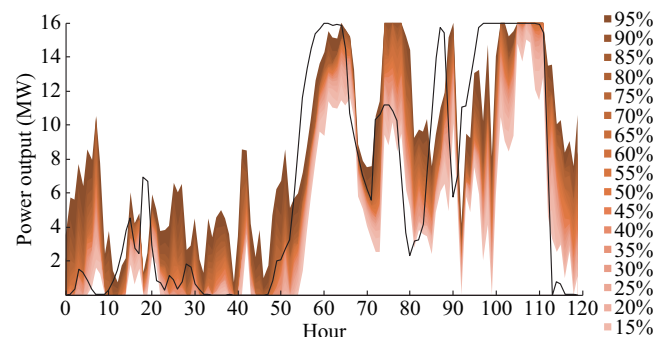


Fig. 1. Wind power probabilistic forecasting.

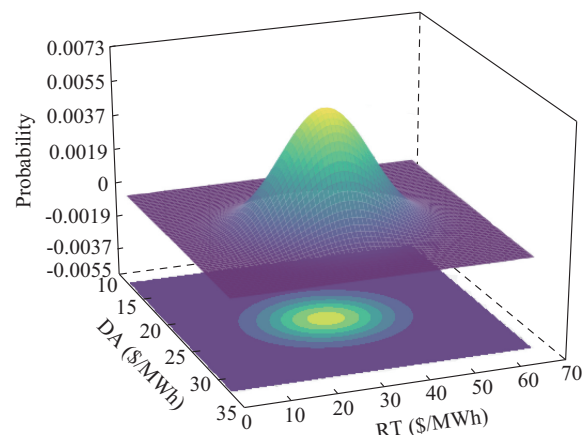


Fig. 2. Joint probabilistic density function of DA and RT forecasted LMPs.

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There was previous literature dealing with the wind power offering problems such as [8]. In these studies, a set of probabilistic scenarios were generated to represent the uncertainties of the wind power production and the market prices in which the computation burden dramatically increases with the number of scenarios [9], [10]. In [11], the optimal wind offer quantity was derived directly from wind power probabilistic forecasting. In this paper, only the wind production uncertainty is considered, and the forward prices and deviation penalty prices are deterministic.

In this paper, an analytical method to obtain the optimal wind offering for the DA market is proposed considering both the uncertainties of wind power production and the LMP forecasting of the DA and RT markets. The main contributions of this paper are twofold: ① both the uncertainties of wind power forecasting and electricity price forecasting are considered using the probabilistic density functions of forecasting; ② the correlation between the DA and RT prices are analytically modeled instead of generating a set of scenarios.

The rest of this paper is organized as follows: Section II proposes the method to obtain the optimal wind offered quantity considering the uncertainties of wind production and LMP forecasting; Section III performs the case study with the actual MISO historical LMP data; and Section IV concludes the paper.

II. STRATEGIC WIND OFFERING IN TWO-PRICE MECHANISM MARKETS WITH CORRELATED UNCERTAINTIES

The wind power deviation is settled with the two-price mechanism [6]. The power shortage and power excess are settled with the DA or RT LMPs based on the deviation directions. The expected revenue of this mechanism is shown in (1).

$$E(R) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{\pi_{DA}, \pi_{RT}}(\pi_{DA}, \pi_{RT}) \left[P_{DA} \pi_{DA} + \int_0^{P_{DA}} f(P_{RT}) \pi_{RT}^+(P_{RT} - P_{DA}) dP_{RT} + f(P_{RT}) \pi_{RT}^-(P_{RT} - P_{DA}) dP_{RT} \right] d\pi_{RT} d\pi_{DA} \quad (1)$$

$$\pi_{RT}^+ = \max(\pi_{RT}, \pi_{DA}) = \begin{cases} \pi_{RT} & \pi_{RT} \geq \pi_{DA} \\ \pi_{DA} & \pi_{RT} < \pi_{DA} \end{cases} \quad (2)$$

$$\pi_{RT}^- = \min(\pi_{RT}, \pi_{DA}) = \begin{cases} \pi_{DA} & \pi_{RT} \geq \pi_{DA} \\ \pi_{RT} & \pi_{RT} < \pi_{DA} \end{cases} \quad (3)$$

where R is the revenue of the wind power owner; π_{DA} and π_{RT} are the DA and RT forecasted LMPs, respectively; $E(X)$ is the expectation of random variable X ; P_{DA} is the wind power quantity in the DA market; P_{RT} is the wind power output in the RT market; $f(P_{RT})$ is the probability distribution function (PDF) of forecasted wind power output; π_{RT}^+ and π_{RT}^- are the penalties for the wind power positive and negative deviations, respectively; and $f_{\pi_{DA}, \pi_{RT}}(\pi_{DA}, \pi_{RT})$ is the joint PDF for DA and RT LMPs.

Assume that the DA and RT LMPs are independent of the wind power. The first order derivative of (1) to the offered DA wind power quantity is given as (4).

$$\begin{aligned} \frac{\partial E(R)}{\partial P_{DA}} = & \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{\pi_{DA}, \pi_{RT}}(\pi_{DA}, \pi_{RT}) \left[\pi_{DA} + f(P_{RT}) \pi_{RT}^+(P_{RT} - P_{DA}) - \right. \\ & \left. \int_0^{P_{DA}} f(P_{RT}) \pi_{RT}^+ dP_{RT} - f(P_{RT}) \pi_{RT}^-(P_{RT} - P_{DA}) - \right. \\ & \left. \int_{P_{DA}}^{P_{max}} f(P_{RT}) \pi_{RT}^- dP_{RT} \right] d\pi_{RT} d\pi_{DA} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{\pi_{DA}, \pi_{RT}}(\pi_{DA}, \pi_{RT}) \cdot \\ & [\pi_{DA} - \pi_{RT}^+ F(P_{DA}) - \pi_{RT}^- (1 - F(P_{DA}))] d\pi_{RT} d\pi_{DA} = \\ & \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{\pi_{DA}, \pi_{RT}}(\pi_{DA}, \pi_{RT}) [\pi_{DA} - \pi_{RT}^- - F(P_{DA}) (\pi_{RT}^+ - \pi_{RT}^-)] d\pi_{RT} d\pi_{DA} \end{aligned} \quad (4)$$

where $F(P_{DA})$ is the cumulative probability function.

The optimal condition for the wind power offering is formulated as:

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{\pi_{DA}, \pi_{RT}}(\pi_{DA}, \pi_{RT}) [\pi_{DA} - \pi_{RT}^- - F(P_{DA}) (\pi_{RT}^+ - \pi_{RT}^-)] d\pi_{RT} d\pi_{DA} = 0 \quad (5)$$

Based on (2) and (3), (5) can be reformulated as:

$$\pi_{RT}^+ - \pi_{RT}^- = |\pi_{RT} - \pi_{DA}| \quad (6)$$

$$E(\pi_{DA}) - E(\pi_{RT}^-) - F(P_{DA}) E(|\pi_{RT} - \pi_{DA}|) = 0 \quad (7)$$

Finally, the offered optimal wind quantity is decided by:

$$F(P_{DA}) = \frac{E(\pi_{DA}) - E(\pi_{RT}^-)}{E(|\pi_{RT} - \pi_{DA}|)} \quad (8)$$

If π_{RT} and π_{DA} are Gaussian distributed random variables, the expectation of $E(\pi_{RT}^-)$ is determined by (9) [12] and $E(|\pi_{RT} - \pi_{DA}|)$ is shown in (11).

$$E(\pi_{RT}^-) = \mu_{\pi_{RT}} \Phi\left(\frac{\mu_{\pi_{DA}} - \mu_{\pi_{RT}}}{\theta}\right) + \mu_{\pi_{DA}} \Phi\left(\frac{\mu_{\pi_{RT}} - \mu_{\pi_{DA}}}{\theta}\right) - \theta \phi\left(\frac{\mu_{\pi_{DA}} - \mu_{\pi_{RT}}}{\theta}\right) \quad (9)$$

$$\theta = \sqrt{\sigma_{\pi_{DA}}^2 + \sigma_{\pi_{RT}}^2 - 2\rho\sigma_{\pi_{DA}}\sigma_{\pi_{RT}}} \quad (10)$$

$$E(|\pi_{RT} - \pi_{DA}|) = \frac{\theta\sqrt{2}}{\sqrt{\pi}} e^{-\left[\frac{(E(\pi_{RT}) - E(\pi_{DA}))^2}{2\theta^2}\right]} + (E(\pi_{RT}) - E(\pi_{DA})) \left[1 - 2\Phi\left(\frac{\mu_{\pi_{DA}} - \mu_{\pi_{RT}}}{\theta}\right)\right] \quad (11)$$

where $\mu_{\pi_{DA}}$ and $\mu_{\pi_{RT}}$ are the means of DA and RT LMPs, respectively; $\sigma_{\pi_{DA}}$ and $\sigma_{\pi_{RT}}$ are the standard deviations of DA and RT LMPs, respectively; ρ is the correlation coefficient of LMPs; Φ and ϕ are the cumulative probability function (CDF) and PDF of Gaussian distribution, respectively; and θ is the standard deviation of $\pi_{RT} - \pi_{DA}$ considering the correlation. Note that the Gaussian distribution assumption of π_{RT} and π_{DA} means that the forecasting errors of electricity prices follow Gaussian distribution. It does not mean that the actual historical market prices follow Gaussian distribution. This assumption for price forecasting is used in lots of literature.

III. CASE STUDY

In this section, the proposed wind power DA offering method is tested using the historical DA hourly and RT 5-

minute price data from MISO and the Michigan Hub data [13]. A 115-MW wind power plant assembled from Wind Toolkit [14] is used. The quantile regressive probabilistic forecasting method [15] is used to obtain the wind power probabilistic forecasting results. The tests were performed from December 11 to 15 in 2016. The expectations of DA and RT price are shown in Fig. 3. The standard deviations of the forecasted DA and RT prices are 10% and 30% of their means, respectively. The optimal quantile values for the DA offering and the actual wind power offering are shown in Fig. 4 and Fig. 5 with different correlation coefficients between the DA and RT LMP forecasting errors. After obtaining the DA offering, the actual wind power output is used to calculate the wind revenue with 20000 samples for the uncertain DA and RT LMPs. Figure 6 demonstrates the revenue results such as the value at risk (VaR), conditional VaR (CVaR) under 95% confidence level [8], [16] and the expected revenue with different correlation coefficients.

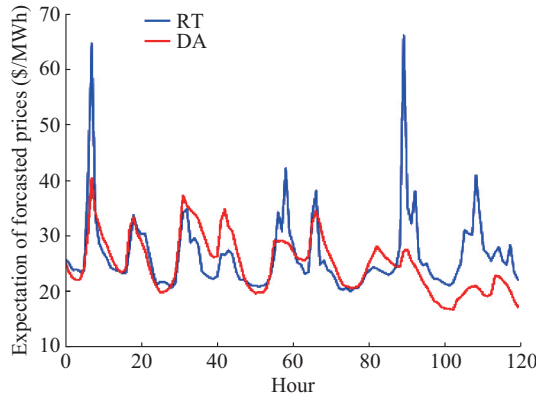


Fig. 3. Expectation of DA and RT prices.

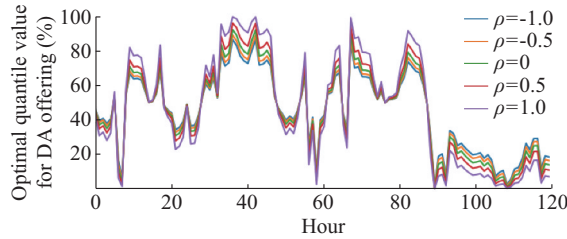


Fig. 4. Optimal quantile values for DA offering with different LMP correlation coefficients.

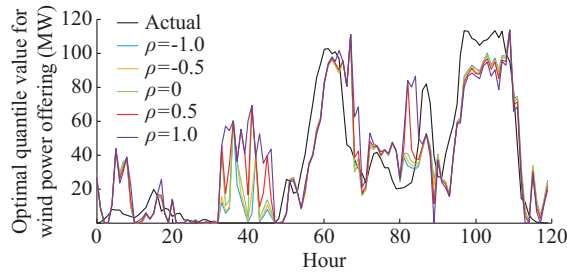


Fig. 5. Wind power offering with different DA and RT LMP correlation coefficients.

Figure 4 and Fig. 5 show that the wind power is prone to offer a high quantity in the DA market when the DA price

expectation is higher than the RT price. In contrast, when the RT market has a higher price expectation, the wind power DA offering is low. Both Fig. 4 and Fig. 5 demonstrate that the wind power offering changes with the correlation coefficient between the DA and RT LMP forecasting errors. In a higher correlation scenario, the wind power will offer a higher amount during the 8th to 17th, 28th to 47th, and 61th to 86th hours. In contrast, during the remaining hours, the wind power offering decreases with the correlation coefficient. The first order derivative of (8) to the correlation coefficient ρ is shown in (12). When the sign of $\partial F(P_{DA})/\partial \rho$ is positive, the wind offering increases with ρ ; when this sign is negative, the wind offering decreases with ρ .

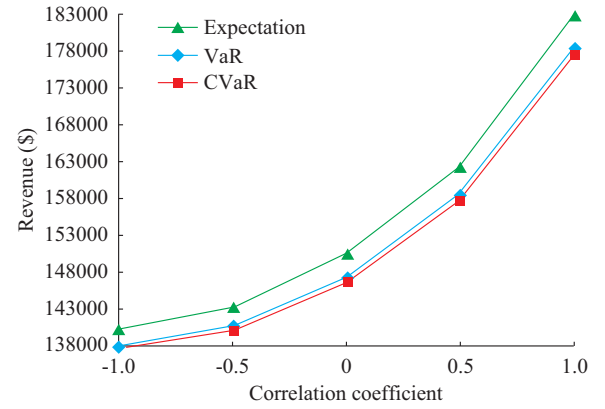


Fig. 6. Wind revenue results with different DA and RT LMP correlation coefficients.

$$\frac{\partial F(P_{DA})}{\partial \rho} = -\frac{\partial E(\pi_{RT}^-)}{\partial \rho \cdot E(\pi_{RT}^- - \pi_{DA})} - [E(\pi_{DA}) - \frac{\partial E(\pi_{RT}^-)}{\partial \rho \cdot E(\pi_{RT}^- - \pi_{DA})}] \quad (12)$$

$$\frac{\partial E(\pi_{RT}^-)}{\partial \rho} = \left[-\mu_{\pi_{RT}} \Phi' \left(\frac{\mu_{\pi_{DA}} - \mu_{\pi_{RT}}}{\theta} \right) \frac{\mu_{\pi_{DA}} - \mu_{\pi_{RT}}}{\theta^2} - \mu_{\pi_{DA}} \Phi' \left(\frac{\mu_{\pi_{RT}} - \mu_{\pi_{DA}}}{\theta} \right) \frac{\mu_{\pi_{RT}} - \mu_{\pi_{DA}}}{\theta^2} - \phi' \left(\frac{\mu_{\pi_{DA}} - \mu_{\pi_{RT}}}{\theta} \right) \frac{\mu_{\pi_{DA}} - \mu_{\pi_{RT}}}{\theta} + \phi \left(\frac{\mu_{\pi_{DA}} - \mu_{\pi_{RT}}}{\theta} \right) \right] \frac{\sigma_{\pi_{DA}} \sigma_{\pi_{RT}}}{\theta} \quad (13)$$

Figure 6 shows that the VaR, CVaR and the expectation of revenue increase with the correlation coefficients between the DA and RT LMP forecasting errors. For instance, the revenue expectation increases by 30.18% from \$140241.20 to \$182569.50 when the correlation coefficient increases from -1 to 1 . Figure 3 shows that there is a positive correlation ($\rho = 0.5$) between the DA and RT prices. Thus, in the wind power offering, this price correlation between the DA and RT markets should be considered to obtain the optimal wind power offering, which improves the revenue of wind power producers.

IV. CONCLUSION

In this paper, a model of strategic wind power offering in the DA market is proposed considering the uncertainties of both wind power production and the price forecasting of the DA and RT markets. The optimal wind power offering is derived based on the wind power probabilistic forecasting and the Gaussian distribution assumption for the DA and RT price forecasting errors. The simulation results demonstrate that the correlation coefficients between the DA and RT LMP forecasting errors has a significant impact on the DA wind offering. Therefore, in the market operation, the wind power producers should consider the correlation between the price forecasting of the DA and RT markets through the proposed method.

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