Risk Management and Optimal Bidding for a Wind Power Producer

A. Botterud, *Member, IEEE*, J. Wang, *Member, IEEE*, R.J. Bessa, H. Keko, *Member, IEEE*, V. Miranda, *Fellow, IEEE*

***Abstract*—This paper discusses risk management, contracting, and bidding for a wind power producer. A majority of the wind power in the United States is sold on long-term power purchase agreements, which hedge the wind power producer against future price risks. However, a significant amount is sold as merchant power and therefore is exposed to fluctuations in future electricity prices (day-ahead and real-time) and potential imbalance penalties. Wind power forecasting can serve as a tool to increase the profit and reduce the risk from participating in the wholesale electricity market. We propose a methodology to derive optimal day-ahead bids for a wind power producer under uncertainty in realized wind power and market prices. We also present an initial illustrative case study from a hypothetical wind site in the United States, where we compare the results of different day-ahead bidding strategies. The results show that the optimal day-ahead bid is highly dependent on the expected day-ahead and real-time prices, and also on the risk preferences of the wind power producer. A deviation penalty between day-ahead bid and real-time delivery tends to drive the bids closer to the expected generation for the next day.**

***Index Terms*—Wind power, electricity markets, risk management, contracting, forecasting, bidding, stochastic simulations.**

NOMENCLATURE

The following symbols are used in the paper:

π_h^m	projected operating profit, hour h (h = 1…24), scenario m (m = 1...M) [US$]
$q_{DA,h}$	quantity bid into day-ahead market, hour h [MW]
$q_{RT,h}^m$	quantity bid into real-time market, hour h [MW]
$q_{d,h}^m$	quantity delivered, hour h, scenario m [MW]
$p_{DA,h}^m$	projected day-ahead price, hour h, scenario m [US$/MWh]
$p_{RT,h}^m$	projected real-time price, hour h, scenario m [US$/MWh]
$prob_m$	probability of scenario m
pen_{RT}^{+}	penalty multiplier (<1) for positive deviations between real-time bid and delivery
pen_{RT}^{-}	penalty multiplier (>1) for negative deviations between real-time bid and delivery
pen_{DA}	penalty for deviation between day-ahead bid and real-time delivery [US$/MWh]
$U_h^m(\pi_h^m)$	utility, hour h, scenario m
β	risk parameter in utility function
$CVAR_h$	conditional value at risk, hour h
th	threshold for CVAR
w	weight assigned to CVAR

I. INTRODUCTION

Different countries and regions are introducing policies aimed at lowering the environmental footprint from the energy sector and increasing the use of renewable energy. For instance, the European Union is trying to implement its ambitious 20/20/20 targets by 2020, which aim at reducing greenhouse gas emissions by 20% (compared to 1990 emissions), increasing the amount of renewable energy to 20%, and reducing the overall energy consumption by 20% through energy efficiency [1]. In the United States, a number of initiatives have been taken at the state level, from renewable portfolio standards [2] to regional greenhouse gas emission control schemes. Within the federal government, new energy and environmental policies and goals are also currently being considered, such as a cap-and-trade program for climate emissions and a renewable energy standard. These policies are likely to substantially increase the use of renewable energy. Many other countries, including China and India, are also focusing on increasing the amount of renewable energy in their electricity supply.

The global installed capacity of wind power is increasing rapidly, with a total of 120.8 GW installed at the end of 2008 [3]. The United States, Germany, Spain, and China are the leading countries in terms of installed wind capacity, with the United States and China seeing the largest additions of new capacity in 2008. In a recent report [4], the U.S. Department of Energy (DOE) describes a model-based scenario, where wind energy provides 20% of the U.S. electricity demand in 2030. The report argues that this is feasible and discusses a set of technical and economic challenges that have to be overcome for this scenario to unfold.

With the rapid increase in wind power capacity, it becomes increasingly important to find optimal strategies for wind power producers to sell their generation into the electricity

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A. Botterud and J. Wang are with Argonne National Laboratory, USA (e-mails: abotterud@anl.gov, jianhui.wang@anl.gov).

R.J. Bessa (supported by FCT - Fundação para a Ciência e Tecnologia PhD Scholarship SFRH/BD/33738/2009), H. Keko, and V. Miranda are with INESC Porto and Faculty of Engineering of the University of Porto, Portugal (e-mails: rbessa@inescporto.pt, hkeko@inescporto.pt, vmiranda@inescporto.pt).

market. Financial risk management is therefore an important tool for finding the optimal balance between risk and return. The optimal strategy depends not only on the risk preferences of the producer, but also on the requirements of the financing institutions. So far, most of the wind power in the United States has been sold on long-term power purchasing agreements (PPAs). However, there is an increasing interest in merchant wind generation, and some of the U.S. wind generation is already being sold directly into the day-ahead and real-time electricity markets [5].

In this paper, we discuss risk management, contracting, and bidding for wind power producers. We first give a brief overview of PPAs, and discuss the risk involved in selling wind power through PPAs. In Section III, we give a brief introduction to wind power forecasting and with particular focus on how uncertainty can be represented in wind power forecasts. Section IV discusses optimal bidding of wind power in the electricity market. In particular, we focus on how wind power producers can take advantage of wind power forecasting when bidding into the electricity market. We also propose a mathematical model for optimal wind power bidding under uncertainty in wind generation, day-ahead and real-time prices. Section V present results from a case study from a wind power site in the United States. We conclude by summarizing the main findings in the discussion and case study.

II. Power Purchasing Agreements (PPAs)

PPAs are long-term contracts between a wind power producer and a purchaser of wind power. In the United States, about 70% of the installed wind power through 2008 was sold through a PPA, with investor-owned utilities being the most frequent purchaser of PPAs, followed by publicly owned utilities and power marketers [5]. The PPA determines the price for delivered wind power for a long time period, typically 20 years. The development of energy prices for wind power PPAs is discussed in [5] and shown in Fig. 1. Note that these prices include state and federal incentives, such as renewable energy credits (RECs) and the wind power production tax credit (PTC).[1] The PPA prices have risen somewhat over the last few years, mainly due to the higher cost of materials. The prices can be compared to the current cost of building new wind capacity, as estimated in [4] and shown in Fig. 2. When comparing the two figures, and adjusting for the financial incentives included in the PPA prices in Fig. 1 (the current PTC is US$21/MWh), we see that wind PPA prices are within the lowest range of the estimated levelized cost of wind energy.

[1] Specific incentives for investments in renewable generation, such as renewable energy standards (RES), RECs, and the PTC add important revenue on top of the income from energy sales for wind power producers. In the United States, the PTC is a national program, whereas other incentives vary among the states.

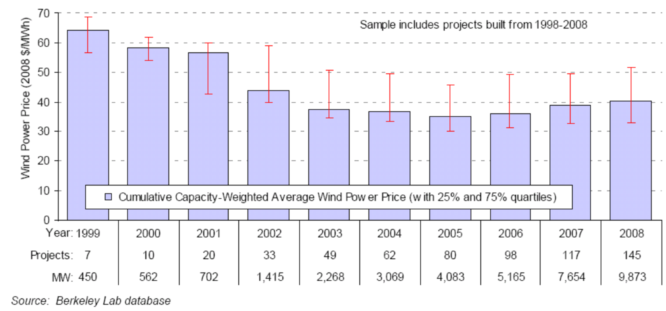

Fig. 1. Cumulative capacity-weighted average wind power prices for PPAs, 1999–2008. Source: [5].

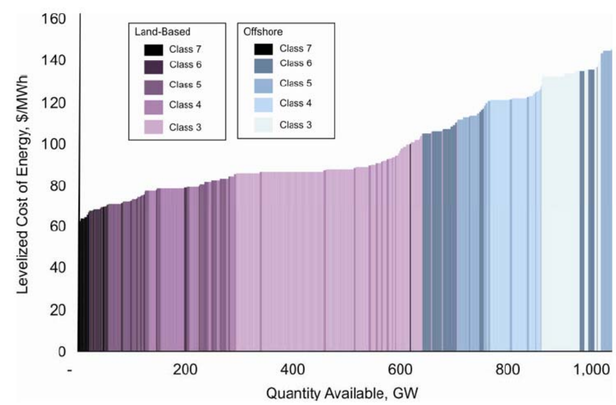

Fig. 2. Supply curve for wind energy, including transmission access cost, but excluding production tax credits and other incentives. Source: [4].

In addition to specifying the price for delivered wind power, which could either be fixed or vary by time, the PPA also determines a number of other conditions for the sales of wind power. According to [6], the PPA typically specifies the terms for important issues such as the length of the agreement, the commissioning process, the purchase and sale of energy, curtailment agreements, transmission issues, milestones and defaults, credit, insurance, and environmental attributes or credits. The exact risk exposure of the wind power producer depends on the terms of the individual PPAs. However, although the price is fixed by the PPA, in most cases the producer still faces considerable risk in terms of the quantity of wind power produced from the wind farms.

III. Wind Power Forecasting and Scenario Generation

An advanced wind power forecasting system uses input data from different sources, including results from numerical weather prediction models (NWPs), local meteorological measurements, SCADA data (i.e., active power generated), and additional information about the characteristics of the wind power plants and the nearby terrain and topography. The performance of wind power forecasts and the forecast accuracy depend on several factors, e.g., NWP forecasts, complexity of the terrain, and the availability of real-time weather and power plant data. There can be large differences in forecasting errors between wind power plants at different locations. Wind power forecasting systems typically produce forecasts for a time horizon between 1 hour and 2–3 days ahead in time. In general, the forecasting error increases with the forecast horizon. A detailed description of state-of-the art wind power forecasting is provided in [7].

The uncertainty in the wind power forecast is obviously of importance for a wind power producer bidding into the electricity market, since the realized wind generation to a large extent determines the profits. There are several different approaches for modeling uncertainty in the projected wind power, as explained in [7], including probabilistic representations, risk indices, and scenarios. In this paper, we use the approach described in [8] to produce probabilistic forecasts based on the wind power point forecast errors. The model employs a linear quantile regression with the base functions formulated as cubic B-splines in order to obtain the quantile with a proportion of the forecast errors. In [8], each quantile is modeled as a sum of the nonlinear smooth functions of the forecasted wind power generation. Spline bases are used to approximate each of the smooth functions as a linear combination of base functions. The probabilistic forecast is represented through a set of quantiles ranging from 0.05 to 0.95 with a 0.05 increment.

The method described in [9] is used to generate a number of wind power scenarios that provide information on the dependency of the prediction errors through the set of look-ahead times. The method is based on the conversion of the set of random variables composing probabilistic forecast series, as obtained with the quantile regression method described above, into a multivariate Gaussian random variable. The temporal interdependence structure is represented by the covariance matrix, which is recursively estimated because of the nonstationary characteristics. Monte Carlo simulation is used for the generation of equiprobable scenarios. Illustrations of the resulting forecast quantiles (which are equivalent to forecast intervals) and scenarios are provided in Fig. 3 and Fig. 4. The forecasts in the two figures are used in the case study in Section V.

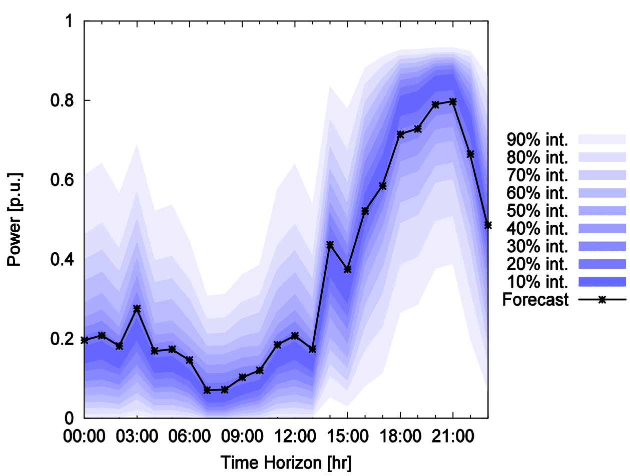

Fig. 3. Probabilistic representation of wind power forecast as intervals or quantiles.

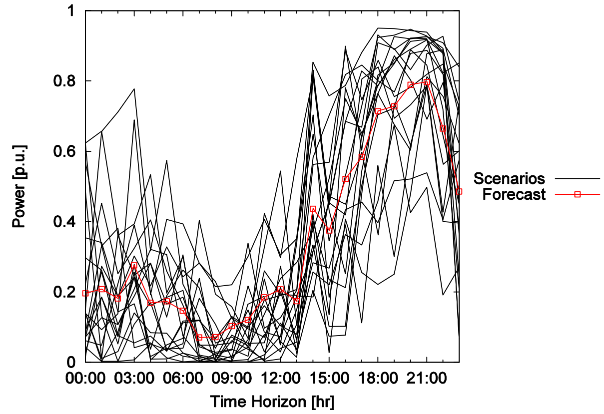

Fig. 4. Forecast scenarios of wind power generation.

IV. Optimal Bidding in the Wholesale Market

Wind power producers may benefit from increased profits, possibly at the expense of higher risk, by participating in the wholesale electricity market instead of selling their generation in PPAs. The potential benefits of participating in the short-term markets obviously depend on the development of market prices compared to the prices of PPAs. However, the strategy for bidding in the day-ahead and real-time markets will also influence revenues, imbalance costs, and affect the overall profit for the wind power producer.

Bidding and trading of wind power in short-term electricity markets is still a relatively new problem. Some analytical approaches to the problem have been proposed in [10] [11] [12], with applications to electricity markets in Europe. The focus in these approaches is to minimize the imbalance costs from trading wind energy. The imbalance costs, in turn, depend on the rules governing dispatch and financial settlement in the respective electricity market. In this paper, we focus on bidding of wind power in the context of U.S. electricity markets. An overview of how wind power is currently handled in U.S. electricity markets can be found in [13], whereas [14] contains a discussion on the role of wind power forecasting in market operations. Many of the system operators (ISO/RTOs) are working on revising their current rules to better accommodate wind power. Additional changes in the market designs and settlement rules are therefore likely to emerge, as more wind power is introduced in different regions of the United States. In our analysis of bidding strategies, we base our assumptions on current rules representative for some U.S. markets.

Below, we present a simple mathematical model for optimal bidding of wind power in the electricity market. We use scenarios to represent the forecast uncertainty, as discussed in Section III. The scenarios are used to calculate probability distributions for the wind power producer's profit as a function of different bidding strategies, also taking into account uncertainty in market prices. Uncertainties in hourly wind power generation, day-ahead prices, and real-time prices are all represented in terms of scenarios. Note that the scenario representation allows for the representation of correlation between the random variables, as long as this is taken into account in the scenario generation.

A. Wind Power Profits

First, let us assume that the wind power producer can bid into the day-ahead market and is allowed to revise its bids ahead of the real-time market clearing. There is a penalty for deviations between the real-time bid and the delivered generation. The resulting profit of the wind power producer for one realization of scenarios for wind power and prices, π_h^m, is shown in (1):

$$\pi_h^m = p_{DA,h}^m \cdot q_{DA,h} + p_{RT,h}^m \cdot \left(q_{RT,h}^m - q_{DA,h}\right) + p_{RT,h}^m \cdot pen_{RT} \cdot \left(q_{d,h}^m - q_{RT,h}^m\right) \tag{1}$$

where pen_{RT} is equal to $pen_{RT}^{+}/pen_{RT}^{-}$ if the deviation in real-time delivery, $q_{d,h}^m - q_{RT,h}^m$, is positive/negative.

For the wind power producer there are two decisions, i.e., to determine the amount of power to bid into: (1) the day-ahead market and (2) the real-time market. These two decisions can be regarded as first- and second-stage decisions. The first-stage decision must be based on the best available wind power forecast at the day-ahead stage, whereas the second-stage decision can take advantage of better forecasts available closer to real time. Note that both day-ahead and real-time prices are uncertain at the day-ahead stage, whereas the real-time price is still uncertain at the real-time stage. The optimal bidding strategy at the day-ahead stage therefore depends on the price distributions for both day-ahead and real-time prices, in addition to the wind power forecast. In contrast, the optimal real-time bid will always be to bid according to the best available point forecast for real-time generation, as long as penalties are being charged for deviations from the real-time schedule. The main objective is therefore to find the optimal day-ahead bidding strategy.

Most U.S. electricity markets allow wind power producers to bid into the day-ahead market, but not into the real-time market.[2] A simpler and somewhat more relevant formulation of the wind power producer's profit under current conditions in many markets is therefore shown in (2):

$$\pi_h^m = p_{DA,h}^m \cdot q_{DA,h} + p_{RT,h}^m \cdot \left(q_{d,h}^m - q_{DA,h}\right) + pen_{DA} \cdot \left|q_{d,h}^m - q_{RT,h}^m\right| \tag{2}$$

Under this formulation, the deviation between day-ahead bid and real-time delivery is settled at the real-time price. In addition, a potential penalty is introduced, which depends on the absolute deviation between day-ahead bid and real-time delivery. Note that the wind power producer has an incentive to curtail its generation whenever the real-time price drops below 0, a phenomenon that quite frequently occurs in markets with locational marginal prices and a high penetration of wind power. Modern wind power plants can easily be controlled to shut down their generation in such situations.

[2] However, some electricity markets, like the New York ISO, require that the wind power producers bid into the real-time market based on the system operator's own forecast [15]. At the same time, the wind power producers must follow dispatch signals during constrained conditions in the network. This procedure contributes to relieve system constraints and also prevents wind power producers from being dispatched during negative prices.

B. Day-Ahead Bidding Decision Criteria

If we assume that the wind power producer is risk neutral, the optimal bidding strategy can be derived by maximizing the expected profit, π_h^*, as shown in (3). An alternative formulation, which considers the wind power producers risk preferences, is to maximize the expected utility, U_h^*, as shown in (4). We assume that a standard exponential utility function, $U_h^m(\pi_h^m)$, can be defined for the wind power producer over the range of possible profit outcomes. The risk attitude is determined by a parameter, β, where a positive/negative β refers to risk prone/averse decision maker. Finally, another decision method which also considers the risk preferences of the decision maker, is to consider a balance between mean profit and risk. In this case, we measure the risk in terms of the conditional value at risk [16], i.e., the expected profit below a certain threshold defined by *th*, e.g., the 5% lowest profit outcomes. An objective function, C_h^*, taking into account both expected profit and $CVAR_h$ is shown in (5). The parameter w determines the weight assigned to $CVAR_h$.

$$\pi_h^* = Max_{q_{DA,h}} \sum_{m=1}^{M} prob_m \cdot \pi_h^m(q_{DA,h}) \tag{3}$$

$$U_h^* = Max_{q_{DA,h}} \sum_{m=1}^{M} prob_m \cdot U_h^m(\pi_h^m(q_{DA,h})) \tag{4}$$

where

$$U_h^m = \frac{1}{1-e^{\beta}} \cdot \left[1 - e^{\frac{\beta(\pi_h^m - \pi^{min}}{\pi^{max} - \pi^{min}}}\right]$$

$$C_h^* = Max_{q_{DA,h}} \left\{ \sum_{m=1}^{M} prob_m \cdot \pi_h^m(q_{DA,h}) + w \cdot CVAR_h(q_{DA,h,}, th) \right\} \tag{5}$$

The decision criteria outlined above can all easily be derived from the scenarios for prices and wind power generation. No inter-temporal constraints are considered, so each hour can be analyzed independently. In the initial case study presented below, we illustrate how the decision criteria influence the optimal bidding decisions.

V. Case Study

A. Assumptions

We analyze the bidding of a hypothetical wind farm in the state of Illinois, using data for one historical day (i.e., Monday, October 9, 2006). The hypothetical wind farm lies within the footprint of the Midwest ISO (MISO). The wind power data used are day-ahead wind power point forecasts and realized generation from one location (site 4848) in the National Renewable Energy Laboratory's Eastern Wind Integration and Transmission Study (EWITS) [17]. The EWITS data were produced by combining a mesoscale weather model with a composite power curve for a number of potential sites for wind power farms in the United States. The day-ahead forecasts were generated based on observed forecast errors from four real wind power plants. The resulting Markov chain forecast models for each of the four sites were randomly assigned to the hypothetical sites in the data set to generate day-ahead forecasts. The data methodology is explained in [18].

We use the wind power data (forecasts and realized generation) for the individual site for the period from January to August 2006 to train the quantile regression, as described in Section III. The months from September to December are used as a test dataset. Since the first month is used to initialize the estimation of the covariance matrix only, the scenarios are produced for October, November and December. A total of 1,000 scenarios of wind power generation are generated for each day. We only look at one individual day (i.e. October 9), in this initial illustrative case study. The deterministic point forecast and 10 forecast scenarios are shown in Fig. 5. The figure illustrates that forecast scenarios span a relatively wide range around the point forecast. The underlying quantile distribution for the same day is shown in Fig. 3.

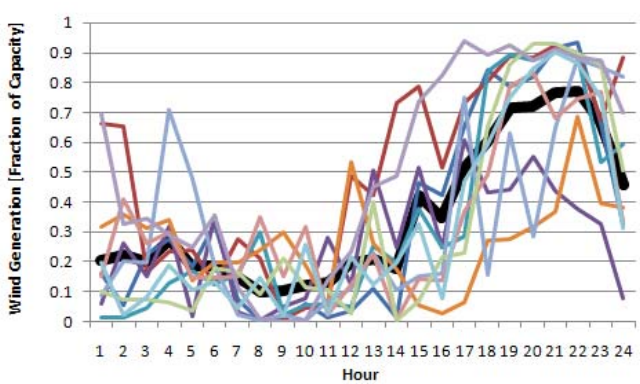

Fig. 5. Deterministic price forecast (solid thick line) and 10 forecast scenarios.

We assume that the wind power producer makes a prediction of day-ahead and real-time prices for the next day, based on the most recent prices observed in the market. Separate price projections are derived for each individual hour. In this initial study, we simply use a normal distribution to represent the uncertainty in the hourly prices.[3] Hourly price means, standard deviations, and correlations between day-ahead and real-time price are obtained from the last 4 weeks ahead of the trading day, separating between weekdays and weekend days. In the initial study, we assume that prices and wind generation are uncorrelated.[4]

We use market price data for weekdays from the 4 weeks before October 9, 2006, from the Illinois trading hub in MISO to estimate the price parameters for each individual hour. Fig. 6 shows that the mean real-time prices are much lower than day-ahead prices at night, whereas the mean real-time price is higher for a few hours during the day. Also, the uncertainty (standard deviation) is much higher in real-time prices than in day-ahead prices. Finally, Monte-Carlo simulation generates 1,000 scenarios for day-ahead and real-time prices for each hour based on the parameters in Fig. 6. The price scenarios are combined with wind power scenarios described above. The resulting set of scenarios is used to evaluate day-ahead bidding, market profits, and risk measures under different decision criteria, as outlined in Section IV. The profit formulation in (2) is used in the analysis, with the assumption that the wind generation is curtailed to zero whenever the real-time price drops below zero. The day-ahead bid quantity can take any value between zero and the installed capacity of the wind farm.

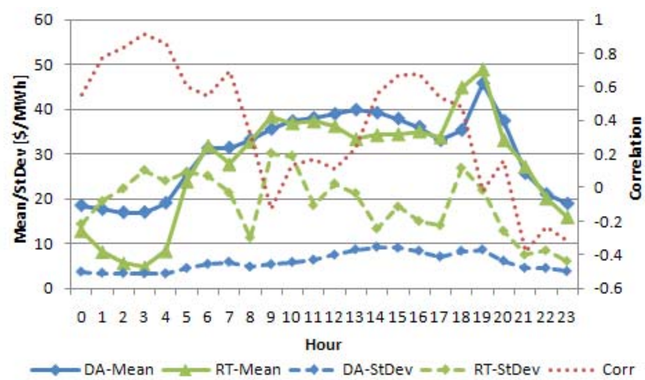

Fig. 6. Estimated day-ahead (DA) and real-time (RT) price parameters.

B. Results

We first present results for one individual hour, looking at how the decision criteria change as a function of day-ahead bid. We then calculate the optimal bidding decisions for all the hours of the day. We analyze the impact of different decision criteria and how a deviation penalty influences the outcome.

For the utility decision criteria in (4), we assume that the risk parameter, β, is either -3 (risk averse) or 3 (risk prone). For the CVAR decision criteria in (5), we assume a CVAR threshold, *th*, of 5% and a weight, *w*, of 0.1.

1) Analysis of bidding in hour 5

In hour 5, the mean day-ahead price is higher than the mean real-time price (US$25.5/MWh vs. US$24.0/MWh), but the standard deviation is higher for the real-time price (25.9 vs. 4.5). The wind power point forecast for hour 5, which represents the projected wind generation for this hour, is 17.4% of installed capacity. Fig. 7 shows that the expected profit (*E*) increases monotonically as a function of the fraction of the capacity bid into the day-ahead market. The higher expected day-ahead price leads the profit maximizer to bid all its quantity into the day-ahead market, since any shortfall in generation can be bought back at the real-time price, which is expected to be lower than the day-ahead price. Hence, the resulting decision does not take into account the expected wind generation for that hour. In contrast, the CVAR criteria add more weight to the lowest profit outcomes. This leads to much less bidding in the day-ahead market in this hour, reducing the exposure to the real-time price. The utility

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[3] The modeling framework based on Monte-Carlo simulations could easily accommodate more advanced price models.

[4] This is clearly a simplifying assumption. In areas with large wind penetration, it is likely to be a negative relationship between the amount of wind generation and the market prices.

criterion (Fig. 8) shows that a risk prone producer will bid the full capacity in the day-ahead market. A risk averse producer would want to bid approximately 40% of capacity into the day-ahead market in hour 5.

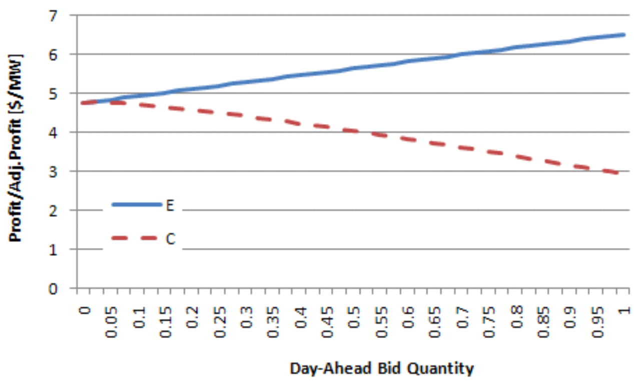

Fig. 7. Expected profit (E) and CVAR criteria (C) as function of day-ahead bid quantity, no deviation penalty.

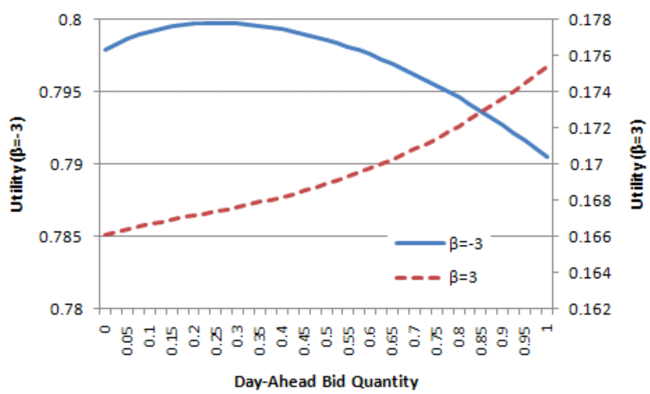

Fig. 8. Expected utility for risk averse (β = -3) and risk prone (β = 3) decision maker, no deviation penalty.

So far, we have assumed that there is no penalty for the deviation between day-ahead bid and real-time delivery. We now repeat the same analysis with a deviation penalty of US$5/MWh. The results are shown in Fig. 9 and Fig. 10. Under the expected profit criterion, the wind power producer now bids much less into the day-ahead market to avoid high deviation penalties. The optimal bid under the CVAR criterion is to increase the day-ahead bid slightly compared to the case without a deviation penalty. The risk averse utility criterion gives less day-ahead bidding. Note that the deviation penalty gives optimal bids much closer to the projected wind generation of 0.174 under all three criteria. In contrast, the risk-prone utility criterion is less concerned with risk of deviation penalties and still finds it optimal to bid all capacity into the day-ahead market.

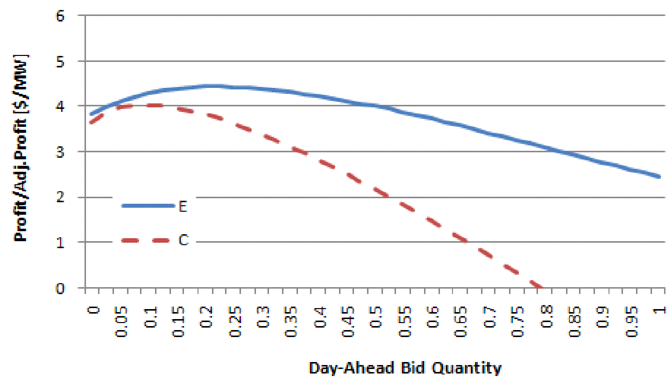

Fig. 9. Expected profit (E) and CVAR criteria (C) as function of day-ahead bid quantity, US$5/MWh deviation penalty.

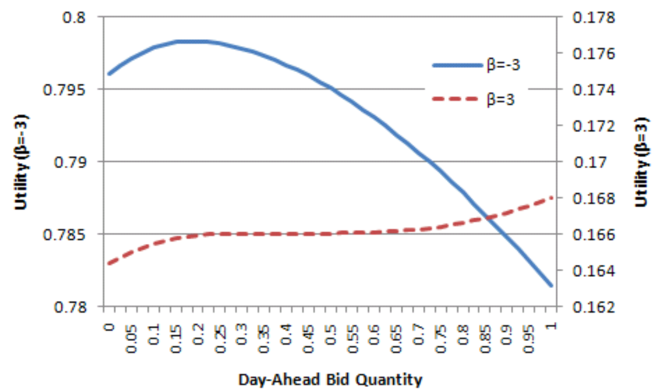

Fig. 10. Expected utility for risk averse (β = -3) and risk prone (β = 3) decision maker, US$5/MWh deviation penalty.

2) Optimal bidding strategies over 24 hours

We now look at the optimal bidding strategy for the entire day (i.e., 24 hours). A search algorithm is used to derive the optimal bids for the different decision criteria. Fig. 11 shows that under the expected profit criterion, the optimal decision is to bid full capacity in the day-ahead market whenever the expected day-ahead price is above the expected real-time price. No capacity is bid into the day-ahead market when the expected real-time price is higher than the expected day-ahead price under this criterion. The risk prone utility criterion gives almost exactly the same results (not included in Fig. 11). With the CVAR and risk-averse utility criteria, the optimal bid is in between the maximum and minimum capacity in hours with a small difference in expected day-ahead and real-time price. The bid quantity tends to be higher with the utility criterion than with the CVAR criterion. Overall, the decision strategies are mainly driven by the price expectations, as long as there is no deviation penalty. A deviation penalty would bring the bids closer to the projected generation (i.e., the point forecast), as shown in the analysis of hour 5.

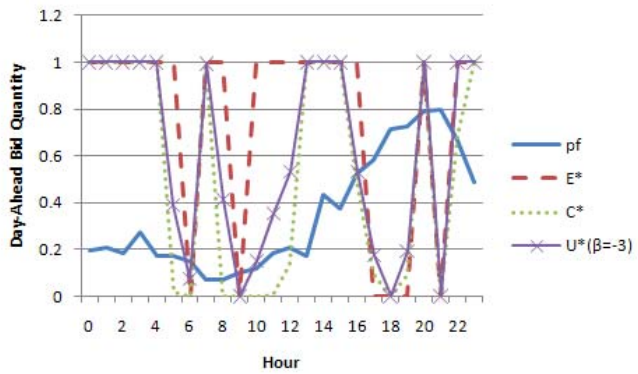

Fig. 11. Optimal day-ahead bidding under different decision criteria for 24 hours. No deviation penalty. *pf* is the point forecast.

VI. Conclusion

Although most wind power generation in the United States is sold on long-term contracts, a significant share of wind generation is sold directly in the electricity market. For this merchant wind generation, it is important to the find the right balance between risk and return when bidding into the electricity market. In a simple case study, we have analyzed the optimal bid quantity in the day-ahead market. The results show that the optimal day-ahead bid is highly dependent on the expected day-ahead and real-time prices, but also on the risk preferences of the wind power producer, as reflected in the decision criteria. A deviation penalty between day-ahead bid and real-time delivery tends to drive the bids closer to the expected generation for the next day.

We would like to emphasize that the analysis presented in this paper is preliminary and built on a number of simplifying assumptions. As we proceed with our research in this area, we will add more realism to the analysis by introducing more advanced price models, which capture the relationship between wind generation and market prices. We will also consider alternative market rules and profit formulations to analyze in greater detail how market design influences the optimal bidding decisions. Another interesting extension of the analysis is to consider the optimal market strategies for a portfolio of assets consisting of other types of generation and possibly also demand resources, in addition to wind power. Finally, we will evaluate the performance of different market strategies by simulating a longer historical time period, and asses the results for realized wind generation.

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IX. Biographies

Audun Botterud received his M.Sc. in industrial engineering (1997) and a Ph.D. in electrical engineering (2003), both from the Norwegian University of Science and Technology. He is an energy systems engineer in the Center for Energy, Environmental, and Economic Systems Analysis (CEEESA) at Argonne National Laboratory. He was previously with SINTEF Energy Research in Trondheim, Norway. His research interests include power system planning and economics, renewable energy systems, wind power integration, stochastic optimization, and agent-based modeling.

Jianhui Wang received his B.S. degree in management science and engineering (2001) and a M.S. degree in technical economics and management (2004), both from North China Electric Power University, China, and his Ph.D. in electrical engineering from Illinois Institute of Technology, USA (2007). Presently, he is an assistant computational engineer - Energy Systems with CEEESA at Argonne National Laboratory. His research interests include energy economics and policy, agent-based modeling and simulation, and electric power systems optimization and economics. He is chair of the IEEE PES power system operation methods subcommittee and co-chair of the task force on integration of wind and solar power into power system operations.

Ricardo J. Bessa received his Licenciado (five years) degree from the Faculty of Engineering of the University of Porto, Portugal (FEUP) in 2006 in electrical and computer engineering. In 2008 he received his Master degree in data analysis and decision support systems from the Faculty of Economy of the University of Porto (FEP). Currently, he is a researcher at INESC Porto in its Power Systems Unit and a PhD student in the Sustainable Energy Systems Program at FEUP. His research interests include wind power forecasting, data mining and decision-aid methods.

Hrvoje Keko graduated in electrical power systems engineering from the Faculty of Electrical Engineering and Computing of the University of Zagreb, Croatia. He is presently a PhD. student enrolled in the Sustainable Energy Systems Program at FEUP - Faculty of Engineering of the University of Porto, Portugal. He is also a researcher at INESC Porto in its Power Systems Unit. His interests include computational intelligence tools, wind power forecasting and impact of electrical transportation in power system planning and operation.

Vladimiro Miranda received his Licenciado, Ph.D. and Agregado degrees from the Faculty of Engineering of the University of Porto, Portugal (FEUP) in 1977, 1982, and 1991, all in electrical engineering. In 1981, he joined FEUP and currently holds the position of Professor Catedrático. He is also currently a Director of INESC Porto, an advanced research institute in Portugal. He has authored many papers and been responsible for many projects in areas related with the application of computational intelligence to power systems.