Bidding Strategy for a Wind Power Producer in US Energy and Reserve Markets

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BIDDING STRATEGY FOR A WIND POWER PRODUCER IN

US ENERGY AND RESERVE MARKETS

by

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Wind power is one of the world's fastest-growing renewable energy resources and has expanded quickly within the US electric grid. Currently, wind power producers (WPPs) may sell energy products in US markets but are not allowed to sell reserve products, due to the uncertain and intermittent nature of wind power. However, as wind's share of the power supply grows, it may eventually be necessary for WPPs to contribute to system-wide reserves. This paper proposes a stochastic optimization model to determine the optimal offer strategy for a WPP that participates in the day-ahead and real-time energy and spinning reserve markets. The objective function maximizes the WPP's total expected profit while minimizing risk by allowing the WPP to split its offers between the energy market and the spinning reserve market, which has lower penalties for failing to deliver the cleared day-ahead offer. Risk is considered through the Conditional Value at Risk metric and several risk aversion levels are studied. Case study results show that the proposed offer strategy increases expected profit and decreases risk compared to the case where the WPP only participates in the energy market.

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PREFACE

Some of the content of this thesis has been published in *Proc. 53rd North American Power Symposium* (A. Stratman, W. Qiao, and L. Qu, "Optimal bidding strategy for a wind power producer in the energy and spinning reserve markets," in *Proc. 53rd North American Power Symposium (NAPS 2021)*, College Station, TX, USA, Nov. 14-16, 2021, pp. 1-6.)

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LIST OF MULTIMEDIA OBJECTS

CHAPTER 1: INTRODUCTION

Wind power is one of the world's fastest growing renewable energy resources, with installed wind capacity reaching 743 GW worldwide by the end of 2020 [1]. The world's two largest wind markets, China and the U.S., together accounted for 75% of new wind capacity installed during 2019. Despite its rapid integration into the global energy supply, wind resources are still unable to provide reserve products due to high forecast uncertainty. As wind power's share of the global energy supply increases, though, wind power producers (WPPs) may replace conventional generators and will need to provide spinning and regulation reserves.

One method of offsetting wind forecast uncertainty is for WPPs to purchase reserves for themselves in the day-ahead (DA) market. Approaches for reserve scheduling include game theory, machine learning, and analytical solutions. For example, reference [2] proposed a bilateral reserve market, in which WPPs purchase reserve power from conventional generators using game theory. Deep reinforcement learning was used to find the optimal quantity of reserves to purchase given the forecast uncertainty in [3], while analytical solutions for the quantity of reserve power a WPP should purchase were derived in [4]. WPPs may also address power production uncertainty by participating directly in the balancing market [5]. However, since real-time (RT) electricity prices tend to be higher than DA prices, purchasing reserves in the RT market may decrease profit compared to the case where the WPP schedules its own reserves. Lastly, WPPs may self-schedule reserves by using a storage system to curtail power for later use [6].

Allowing WPPs to participate in both the DA and reserve markets can increase overall system security and decrease total balancing reserve requirements [7]. Other work has shown that wind power is suitable for providing regulation reserves, and has studied market structures that will encourage WPPs to participate in both the energy and regulation markets [7]-[8]. In [7], probabilistic wind power forecasts were used to determine optimal DA energy and regulation offers. Results showed that imposing lower penalties for deviations in the regulation market than in the energy market encouraged WPPs to submit offers to both. The authors of [8] considered a WPP in the California Independent System Operator (CAISO) market that submits offers to energy and regulation markets. Results showed that the WPP was willing to offer regulation reserves under a similar penalty structure. Additionally, WPPs may indirectly participate in regulation markets by using electrical vehicle batteries to curtail wind power, then selling the curtailed power in the RT regulation market [9]-[10].

WPPs may also participate directly in the spinning reserve market [11]-[13]. Two strategies for offering power in the energy and spinning reserve markets are proposed in [11]: a proportional control strategy, in which the WPP always offers a fixed fraction of its total power output in the reserve market; and a constant control strategy, in which the WPP offers a fixed amount of power in the reserve market only after reaching a minimum threshold of total power production. Under the proportional control strategy, revenue is maximized when the WPP participates fully in either the energy or reserve market; while under the constant control strategy, the optimal bids in each market are given by wind power quantiles that depend on the relationship between the DA/RT energy and reserve prices. Case studies showed that both strategies increased profit compared to participating in only the energy market, but risk was not considered. In [12] the proportional control strategy was implemented using stochastic programming to show that a WPP can successfully provide spinning reserves for a small, islanded power system. Finally, [13] evaluated the proportional control strategy using stochastic optimization. The authors assumed that the WPP could change its offers to each market between the DA and balancing stages, similar to participating in a European adjustment market. Although revenue increased, results showed that the share of power offered the DA/balancing markets sometimes changed significantly between the DA and balancing stages, which could lead to imbalances in systems with high levels of wind power penetration.

This thesis proposes a stochastic optimization model to find the optimal offer strategy for a price-taker WPP who participates in the DA and RT energy and spinning reserve markets. Uncertainty in DA and RT locational marginal prices (LMPs) for energy products, DA/RT market clearing prices (MCPs) for reserve products, and wind power production is considered via scenario generation and reduction. The quantities of power offered to the energy and spinning reserve markets in the DA stage are modeled as stochastic decision variables. The proposed model generates stepwise offer curves for energy and spinning reserves, along with the optimal offers in the RT energy and spinning reserve markets. A case study compares the results of the proposed bidding strategy to the case where the WPP only participates in the energy market. Results show that the proposed model decreases risk while increasing profit for comparable levels of risk-aversion.

Compared to previous work, this thesis proposes a new method of allowing WPPs to participate directly in the spinning reserve market through stepwise offer curves. Other contributions include a novel method of determining the optimal fraction of power to offer to the energy and spinning reserve markets, and a model formulation that allows the WPP to offer excess power in RT to either the energy or spinning reserve market. The proposed model is beneficial from the WPP's perspective, by allowing the WPP to increase profit and decrease risk. The model is also beneficial from the system operator's perspective, since it encourages WPPs to provide spinning reserves to hedge against uncertainty, increasing the total amount of system reserves.

The rest of this thesis is organized as follows: Chapter 2 describes the structure of US electricity markets. Chapter 3 provides the mathematical formulation of the proposed model. Chapter 4 uses a case study to compare the proposed model to the standard case in which the WPP only participates in the energy market, and chapter 5 discusses the conclusions of the thesis.

CHAPTER 2: ELECTRICITY MARKET STRUCTURE

Competitive bidding in US markets takes place during two stages. The first stage is the day-ahead (DA) stage, which takes place 12-36 hours before scheduled power delivery. The second is the real-time (RT) bidding stage, which takes place 5-15 minutes before delivery. During the DA stage, generators submit offer curves consisting of forecasted DA LMPs, and the power production they are willing to offer at each LMP, to the system operator. The system operator clears the offers by balancing the expected system demand and generation. The system operator then returns the cleared offers, or expected hourly power production, to each generator. Generators are paid for their power production up to the cleared DA offer at the DA market price. If the RT power production is less than the cleared DA offer (defined as a negative deviation), the generator must purchase the difference in the RT market at the RT LMP. Similarly, if the RT power production is more than the cleared DA offer (positive deviation), the generator may attempt to its excess generation in the RT market, at the RT LMP.

This thesis adopts the US market structure described above. We assume that the WPP is a price-taker, i.e., its offers do not affect the market prices. The WPP submits stepwise offer curves to the energy and spinning reserve markets, and it is assumed that market participants may offer energy and reserves products during the same hour. This is standard practice in US markets. The ISO co-optimizes the DA energy and reserve offers from all market participants to determine each participant's cleared offer in the energy and reserve markets [14]. The WPP is treated as a conventional power producer, and is therefore subject to penalties if it fails to deliver the entire cleared DA energy/spinning reserve offer in RT. If the WPP defaults on a cleared DA offer (negative deviation), it must purchase energy in the corresponding RT market to fulfill its obligation. However, if the WPP's RT power output is higher than the cleared offer (positive deviation), it may sell the excess power in the RT market.

It is assumed that the WPP may re-offer positive deviations from its cleared DA energy or spinning reserve offer in either the RT energy or spinning reserve market. The WPP may also forego making an offer in the DA stage, and instead offer all power in the RT market. In addition, the WPP cannot change the fraction of its total power output offered to each market between the DA offer stage and RT balancing stage. This ensures that, if the WPP fails to deliver its entire cleared energy or spinning reserve offer, it cannot decrease the corresponding power fraction in RT to avoid incurring a penalty. Finally, it is assumed that the WPP is paid for its spinning reserve capacity regardless of whether the reserves are deployed. This reflects current market practices, and further incentivizes the WPP to provide spinning reserves as a means of hedging against risk [14].

CHAPTER 3: MODEL FORMULATION

The variables and parameters of the objective function and constraints are defined below:

A. Indices and Sets:

t Index for time periods, running from 1 to T

ω, ω' Indices for scenarios, running from 1 to Ω

B. Decision Variables:

$P_{\omega t}^{DA,E}$ Wind power offered in the day-ahead (DA) energy market for scenario ω at time t

$P_{\omega t}^{DA,S}$ Wind power offered in the DA spinning reserve market for scenario ω at time t

$g_{\omega t}$ Fraction of total forecasted power production offered to the energy market in the DA stage

$h_{\omega t}$ Fraction of total forecasted power production offered to the spinning reserve market in the DA stage

$\Delta_{\omega t}^{E1,+}$ Positive real-time (RT) deviation from the DA energy offer, re-offered to the RT energy market, or RT energy offer

$\Delta_{\omega t}^{E2,+}$ Positive RT deviation from the DA energy offer, re-offered to the RT spinning reserve market, or RT spinning reserve offer

$\Delta_{\omega t}^{E,-}$ Negative RT deviation from the DA energy offer

$\Delta_{\omega t}^{S1,+}$ Positive RT deviation from the DA spinning reserve offer, re-offered to the RT energy market, or RT energy offer

$\Delta_{\omega t}^{S2,+}$ Positive RT deviation from the DA spinning reserve offer, re-offered to the RT spinning reserve market, or RT spinning reserve offer

$\Delta_{\omega t}^{S,-}$ Negative RT deviation from the DA spinning reserve offer

$\eta_{\omega t}$ Auxiliary variable used to compute the Conditional Value at Risk (CVaR)

$\varphi_{\omega t}$ Auxiliary variable used to compute the CVaR

C. Random Variables:

$\lambda_{\omega t}^{DA,E}$ DA LMP of energy for scenario ω at time t

$\lambda_{\omega t}^{DA,S}$ DA MCP of spinning reserves for scenario ω at time t

$\lambda_{\omega t}^{RT,E}$ RT LMP for scenario ω at time t

$\lambda_{\omega t}^{RT,S}$ RT MCP for scenario ω at time t

$P_{\omega t}^{F}$ Forecasted wind power production for scenario ω at time t

D. Constants

P^{max} Maximum wind power output

π_{ω} Probability of occurrence of scenario ω

The proposed offer strategy is formulated as follows:

$$Max \sum_{t=1}^{N_T} \sum_{\omega=1}^{N_\Omega} \pi_\omega \{ \lambda_{\omega t}^{DA,E} P_{\omega t}^{DA,E} + \lambda_{\omega t}^{DA,S} P_{\omega t}^{DA,S} + \lambda_{\omega t}^{RT,E} \left(\Delta_{\omega t}^{E1,+} + \Delta_{\omega t}^{S1,+} \right) + \lambda_{\omega t}^{RT,S} \left(\Delta_{\omega t}^{E2,+} + \Delta_{\omega t}^{S2,+} \right) - \lambda_{\omega t}^{RT,E} \Delta_{\omega t}^{E,-} - \lambda_{\omega t}^{RT,S} \Delta_{\omega t}^{S,-} \} + \sum_{t=1}^{N_T} \beta (\eta_t - \frac{1}{1-\alpha} \sum_{\omega=1}^{N_\Omega} \pi_\omega \varphi_{\omega t}) \quad (1)$$

Subject to the constraints:

$$0 \leq P_{\omega t}^{DA,E} \quad (2)$$

$$0 \leq P_{\omega t}^{DA,S} \quad (3)$$

$$0 \leq g_{\omega t} \quad (4)$$

$$0 \leq h_{\omega t} \quad (5)$$

$$g_{\omega t} + h_{\omega t} \leq 1 \quad (6)$$

$$P_{\omega' t}^{DA,E} = P_{\omega t}^{DA,E} : \lambda_{\omega' t}^{DA,E} \quad (7)$$

$$P_{\omega' t}^{DA,S} = P_{\omega t}^{DA,S} : \lambda_{\omega' t}^{DA,S} = \lambda_{\omega t}^{DA,S} \quad (8)$$

$$P_{\omega' t}^{DA,E} \leq P_{\omega t}^{DA,E} : \lambda_{\omega' t}^{DA,E} \leq \lambda_{\omega t}^{DA,E} \tag{9}$$

$$P_{\omega' t}^{DA,S} \leq P_{\omega t}^{DA,S} : \lambda_{\omega' t}^{DA,S} \leq \lambda_{\omega t}^{DA,S} \tag{10}$$

$$\Delta^{E1,+} + \Delta^{E2,+} - \Delta^{E,-} = g_{\omega t} P^{F} - P_{\omega t}^{DA,E} \tag{11}$$

$$0 \leq \Delta_{\omega t}^{E1,+} \tag{12}$$

$$0 \leq \Delta_{\omega t}^{E2,+} \tag{13}$$

$$0 \leq \Delta_{\omega t}^{E1,+} + \Delta_{\omega t}^{E2,+} \leq g_{\omega t} P^{F} \tag{14}$$

$$0 \leq \Delta_{\omega t}^{E,-} \leq P_{\omega t}^{DA,E} \tag{15}$$

$$\left(\Delta_{\omega t}^{E1,+} + \Delta_{\omega t}^{E2,+}\right) \geq 0 \perp \Delta_{\omega t}^{E,-} \geq 0 \tag{16}$$

$$\Delta^{S1,+} + \Delta^{S2,+} - \Delta^{S,-} = h_{\omega t} P^{F} - P_{\omega t}^{DA,S} \tag{17}$$

$$0 \leq \Delta_{\omega t}^{S1,+} \tag{18}$$

$$0 \leq \Delta_{\omega t}^{S2,+} \tag{19}$$

$$0 \leq \Delta_{\omega t}^{S1,+} + \Delta_{\omega t}^{S2,+} \leq h_{\omega t} P^{F} \tag{20}$$

$$0 \leq \Delta_{\omega t}^{S,-} \leq P_{\omega t}^{DA,S} \tag{21}$$

$$\left(\Delta_{\omega t}^{S1,+} + \Delta_{\omega t}^{S2,+}\right) \geq 0 \perp \Delta_{\omega t}^{S,-} \geq 0 \tag{22}$$

$$P_{\omega t}^{DA,E} + P_{\omega t}^{DA,S} + \Delta_{\omega t}^{E1,+} + \Delta_{\omega t}^{E2,+} + \Delta^{S1,+} + \Delta^{S2,+} \leq P^{max} \tag{23}$$

$$0 \leq \varphi_{\omega t} \tag{24}$$

$$\eta_t - \{\lambda_{\omega t}^{DA,E} P_{\omega t}^{DA,E} + \lambda_{\omega t}^{DA,S} P_{\omega t}^{DA,S} + \lambda_{\omega t}^{RT,E}\left(\Delta_{\omega t}^{E1,+} + \Delta_{\omega t}^{S1,+}\right) +$$

$$\lambda_{\omega t}^{RT,S}\left(\Delta_{\omega t}^{E2,+} + \Delta_{\omega t}^{S2,+}\right) - \lambda_{\omega t}^{RT,E}\Delta_{\omega t}^{E,-} - \lambda_{\omega t}^{RT,S}\Delta_{\omega t}^{S,-}\} \leq \varphi_{\omega t} \quad (25)$$

The objective function (1) maximizes the WPP's total expected profit in the DA and RT energy and spinning reserve markets for each operating hour, considering risk through the inclusion of the CVaR term. One of the terms $\Delta_{\omega t}^{E1,+}/\Delta_{\omega t}^{E2,+}$ will always be equal to zero, since in the case of positive deviations, the RT market prices will determine that it is optimal for the WPP to re-offer the entirety of the positive deviation in either the energy market (if $\lambda_{\omega t}^{RT,E} > \lambda_{\omega t}^{RT,S}$) or the spinning reserve market (if $\lambda_{\omega t}^{RT,E} < \lambda_{\omega t}^{RT,S}$). The same applies to $\Delta_{\omega t}^{S1,+}/\Delta_{\omega t}^{S2,+}$. Constraints (2) and (3) enforce non-negativity on the DA energy and spinning reserve offers. Constraints (4)-(6) require that the fractions of forecasted power $g_{\omega t}$ and $h_{\omega t}$ offered in the DA energy and spinning reserve markets, respectively, must be non-negative and less than or equal to the WPP's total forecasted power in each scenario. Constraint (7) enforces non-anticipation for the DA energy offers, i.e., the WPP may not use knowledge of future RT prices to offer different amount of power in the DA stage, for the same DA LMP. Constraint (8) specifies that the offer curves must be non-decreasing, which is a requirement in US electricity markets. Constraints (9)-(10) enforce non-anticipation and non-decreasing offer curves for the DA spinning reserve offers. Constraint (11) imposes that the sum of the positive and negative deviations from the WPP's DA energy offer must be equal to the fraction of power offered in the DA energy market times the forecasted power production, minus the DA energy offer. If the WPP chooses to offer power only in RT, constraint (11) imposes that the power offered may not exceed the forecasted power. Constraints (12) and (13) enforce non-negativity for the positive deviations from the DA energy offer. Constraints (14) and (15) determine the maximum positive and negative deviations from the WPP's DA energy offer, respectively. Constraint (16) imposes that the WPP can have either a positive deviation or a negative deviation from its DA energy offer, but not both. Constraints (17)-(22) apply the same constraints as (11)-(16) to the spinning reserve offers. Constraint (23) ensures that the sum of the WPP's bids in the DA and RT stages does not exceed its maximum power production. Constraints (24)-(25) are used to compute the CVaR for each hour. The CVaR is the weighted average of the expected profit in the least profitable scenarios, defined as the scenarios in the (1 - α)-quantile of the profit distribution [15].

CHAPTER 4: CASE STUDY

The proposed bidding strategy was tested for a WPP that participates in the Southwest Power Pool (SPP) market. The results were compared to the case where the WPP participates only in the energy market. The total installed wind capacity of the WPP was 80 MW. Historical data for DA/RT LMPs and MCPs were obtained from SPP's public database [16], [17]. Historical wind power data were obtained from the National Renewable Energy Laboratory website [18].

The autoregressive integrated moving average (ARIMA) model was used to generate 1000 scenarios for each of the four price types: DA LMPs, DA MCPs, RT LMPs, and RT MCPs [19]. An ARIMA model was also used to generate 1000 scenarios for wind power production [20]. Then, a forward scenario reduction method based on the Kantorovich distance between scenarios was applied to reduce the number of scenarios for each random variable [21]. Based on the tradeoff between accuracy of the results and computation time, the original scenario sets were reduced to five scenarios for each variable. A sample of price and wind power scenarios for one day is shown in Fig. 4.1. For clarity, the mean of the five scenarios for each variable is shown, rather than the scenarios themselves. The scenarios for each individual variable were then combined into tuples to generate 3125 (5^5) scenarios total. All case study simulations were solved using the simplex method, with Gurobi 5.5 and the YALMIP toolbox in MATLAB [22]-

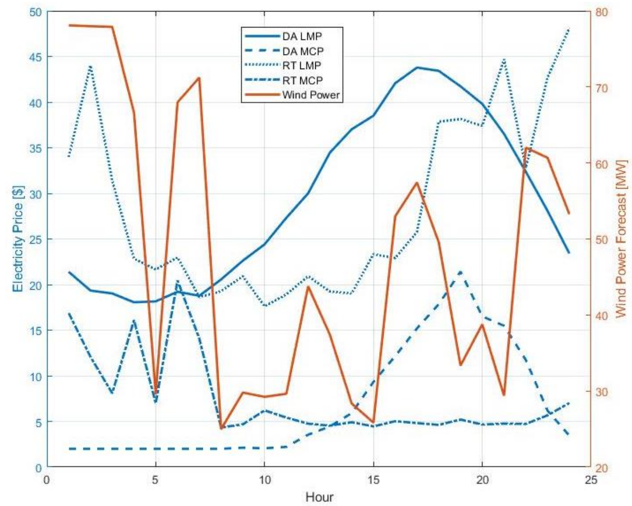

Fig. 4.1: Mean electricity prices and wind power forecast for each hour of one representative day.

[23]. The CVAR confidence interval α was chosen to be 0.95, which corresponds to minimizing the losses in the worst 5% of scenarios.

Fig. 4.2 shows the WPP's expected profit in each market and total expected profit for hours 12-24 of a representative day (the same as Fig. 4.1) under the proposed strategy, compared to the standard case where the WPP only participates in the energy market. For both cases, CVaR weights of β = 0, 0.01, 0.1, 0.2, 0.5, and 1 are shown, where β = 0 corresponds to a risk-neutral WPP (i.e. risk is not considered when determining the bidding strategy); and β = 1 corresponds to the highest level of risk aversion. The top row of plots shows the profit by market for energy bidding only, while the bottom row shows the profit by market for the proposed model. In the top row, the DA energy profit is shown in blue, and the RT energy profit is shown in red. In the bottom row, the DA energy profit is shown in blue, and the DA spinning reserve profit is shown in red. The RT energy profit is shown in yellow, and the RT spinning reserve profit is shown in

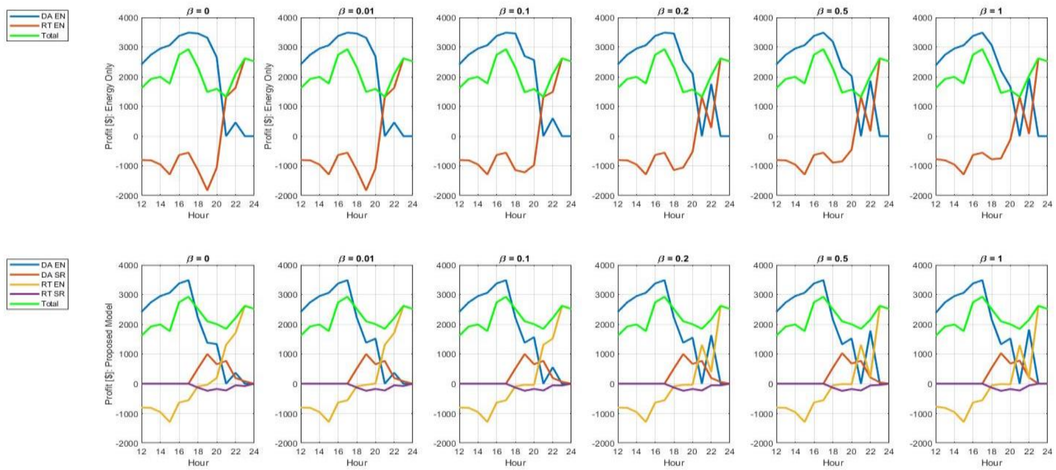

Fig. 4.2: Expected profit per in each market and total profit, for the standard bidding model vs the proposed model.

purple. For both sets of plots, the total profit is shown in green. Positive profit indicates that the WPP successfully delivered its cleared offer, while negative profit indicates that the WPP defaulted on the DA offer, and had to purchase the difference between the cleared offer and the actual generation in the RT market.

Results from both models show that as risk-aversion increases, the WPP's bidding strategy in the DA market changes. For example, for the standard model and $\beta = 0 - 0.01$, the WPP incurs a RT penalty of -\$1850 during hour 19. However, for $\beta \geq 0.1$, the RT penalty during hour 19 goes from -\$1100 to -\$800 as the risk aversion level increases. The WPP's expected DA profit during hour 19 also decreases as risk aversion increases, indicating that the WPP submits smaller bids with a lower risk of default. For the proposed model, the WPP's profit in the spinning reserve markets is the same for all levels of risk aversion. The expected profit in the energy market is the same during hours 1-19. For hours 20-24, as risk aversion increases, the WPP tends to submit a higher bid to the DA energy market and a lower bid to the RT energy market, indicated by the change in expected profit.

Under the proposed model, the WPP can mitigate risk by submitting bids to the DA spinning reserve market, where it will face lower deviation penalties than in the energy market since RT MCPs are generally lower than RT LMPs. For all risk aversion cases, the WPP chooses to offer power in the DA spinning reserve and energy markets during hours 18-22. During these hours, RT LMPs (Fig. 4.1) are relatively high, suggesting that the WPP uses the DA reserve offers to avoid high RT penalties for negative deviations. Under the standard model, the WPP faces large deviation penalties for hours 18-20. However, under the proposed model, the penalties are much smaller or zero. Total expected profit is higher for the proposed model for those hours as well, which suggests that the WPP uses the reserve offers to hedge against the risk of RT penalties and increase its profit.

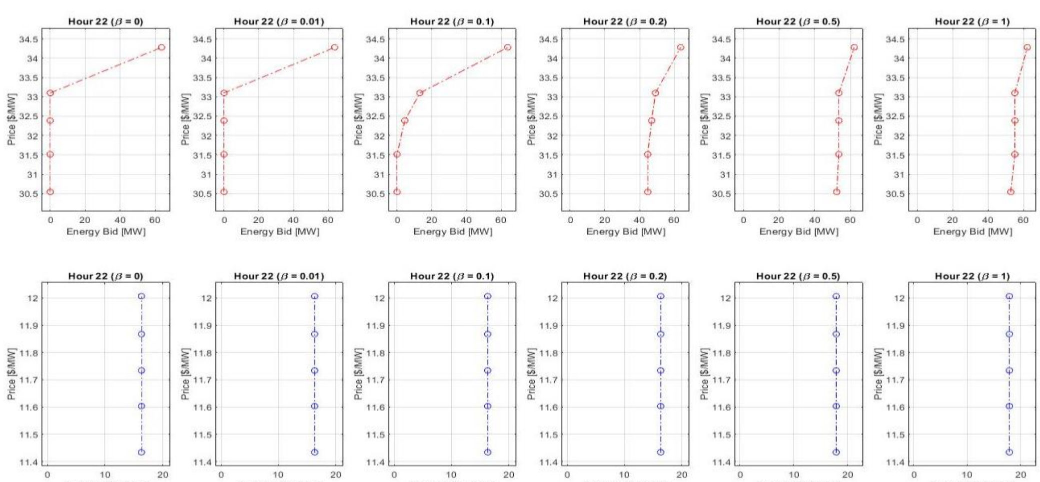

Fig. 4.3: Energy and spinning reserve offer curves for hour 22 with varying levels of risk aversion.

Fig. 4.3 shows the DA offer curves for the energy (top, red) and spinning reserve (bottom, blue) markets for the 22nd hour. The value of the risk aversion parameter β is shown in the plot titles. For the risk-neutral case ($\beta = 0$) the WPP offers nothing in the energy market until the forecasted DA LMP is \$33.50/MW. For higher levels of risk aversion, the WPP submits an offer to the DA energy market at lower prices, since it is less risky to have a guaranteed payoff equal to the DA LMP than to wait to make an offer in the RT stage. For $\beta = 0 - 0.2$, the WPP offers 16 MW to the spinning reserve market, while for $\beta = 0.5 - 1$, the WPP offers 18 MW. This indicates that as the risk-aversion increases, the WPP uses higher reserve bids to decrease the probability of facing high RT penalties in the worst-case scenarios.

Fig. 4.4 compares the energy offer curves from the proposed model (top, red) to the offer curves from energy-only bidding (bottom, blue). The offer strategy for low prices is similar in both cases. However, for higher prices, the WPP offers less in the energy

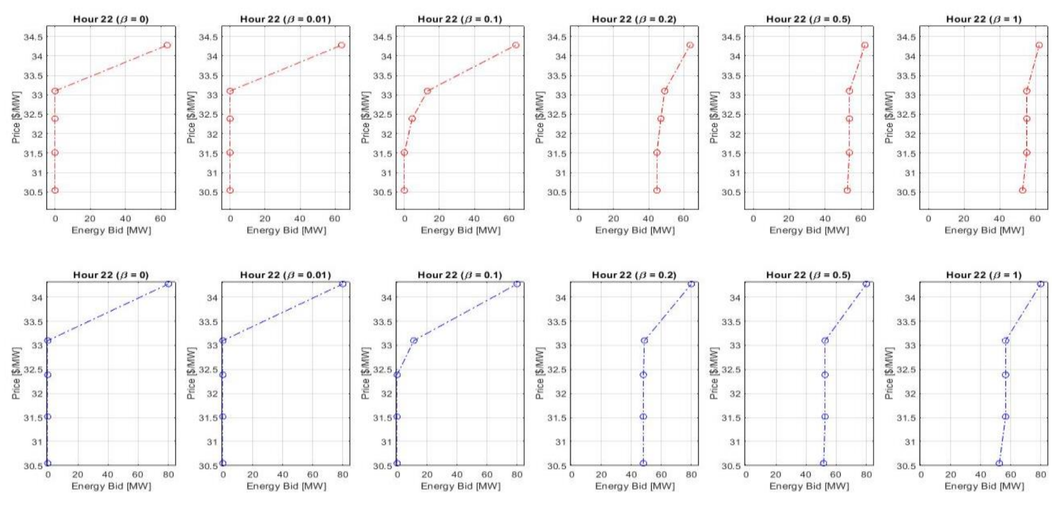

Fig. 4.4: Energy offer curves for the proposed model (top) and standard model (bottom) for hour 22 with varying levels of risk aversion.

market under the proposed model than the standard model. At the highest price point (DA LMP equal to \$34.30/MWh), the WPP offers 62 MW under the proposed model versus 80 MW under the standard model. This is because under the proposed model, the WPP also offers some power to the reserve market, and the sum of both offers must be less than 80 MW. Under the proposed model, as risk aversion increases from $\beta = 0.1$ to $\beta = 0.2$, the WPP submits energy offers to the DA market at lower prices rather than waiting to submit an offer to the RT market. This is the same strategy as the standard model.

Fig. 4.5 compares the CVaR for the standard model (top) versus the proposed model (bottom) for each value of β. The CVaR of hours 1-17 is the same for both models, which is as expected, since the WPP only participates in the energy market during those hours. However, hours 18-22 show how the proposed model is advantageous for

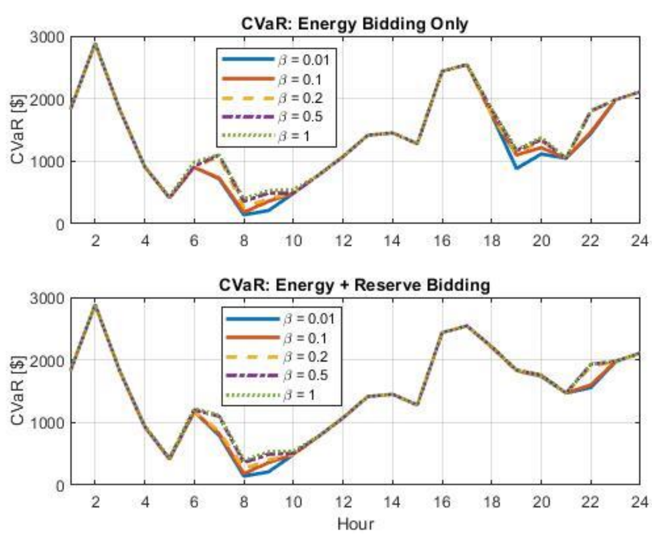

Fig. 4.5: CvaR by hour for the standard and proposed models.

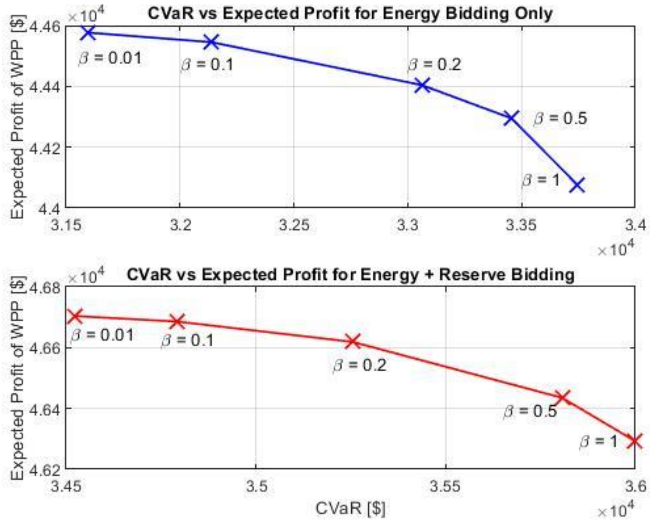

Fig. 4.6: Efficient frontier for the standard and proposed models.

decreasing risk. During hours 18-22, the WPP participates in the energy and spinning reserve markets, and the CVaR is higher than the standard model. For $\beta = 1$ the CVaR increases from ~\$1200 to ~\$1800 during hour 19, and from ~\$1350 to ~\$1800 during hour 20. This shows that during those hours, the WPP successfully uses the spinning reserve market to hedge against economic risk.

Fig. 4.6 plots the efficient frontier of the proposed (top) vs standard (bottom) models. The efficient frontier is the CVaR (x-axis) versus expected profit (y-axis) for each CVaR weight β. The profit and CVaR are summed over the entire representative day under study. For all values of β, both the expected profit and the CVaR are higher for the proposed model are higher than for the standard model. Table 4.1 shows the values of the expected profit and CVaR for the standard model, for each value of β. Table 4.2 shows the same, for the proposed model. The values in Tables 4.1 and 4.2 are also plotted in Fig. 4.6. The results reflect the tradeoff between expected profit and risk aversion. For both cases, as the CVaR weight increases, profit decreases but the CVaR

Table 4.1: Profit and CVaR for the standard model.

β	**0**	**0.01**	**0.1**	**0.2**	**0.5**	**1**
Profit($)	44,577	44,577	44,545	44,404	44,295	44,077
CVaR ($)	N/A	31,594	32,138	33,063	33,454	33,745

Table 4.2: Profit and CVaR for the proposed model.

β	**0**	**0.01**	**0.1**	**0.2**	**0.5**	**1**
Profit($)	46,705	46,704	46,686	46,619	46,435	46,294
CVaR ($)	N/A	34,523	34,791	35,255	35,807	35,988

increases. This indicates that the WPP adopts a more conservative bidding strategy, maximizing the profit in the worst case scenarios while accepting lower profit overall.

CHAPTER 5: CONCLUSION

This paper develops a stochastic optimization model for finding the optimal offer strategy for a WPP that participates in the DA and RT energy and spinning reserve markets. The WPP is allowed to split its total forecasted power production between the energy and reserve markets, and the fractions of power offered to each market are determined through stochastic optimization. Stepwise offer curves for the DA energy and spinning reserve markets are generated, and results show that the optimal strategy sometimes involves participating in both markets. Case study results also show that the proposed bidding strategy increases expected profit and decreases risk compared to the case where the WPP only participates in the DA market; and that the WPP can use the spinning reserve market, in which it faces lower penalties for negative deviations, to hedge against the uncertainty in power production. Finally, the results show that the optimal bidding strategy changes based on the level of risk aversion of the WPP.

From a WPP, providing reserve products can increase profit while decreasing economic risk. Allowing WPPs to provide reserves would be beneficial to system operators as well, since the reserves provided by WPPs would hedge against the uncertainty in wind production and leave other reserve sources free to respond to contingency events. Further research may include incorporating a probability distribution of wind power forecast errors into the optimization model and using the likelihood of default on the DA cleared offer to determine the optimal bidding strategy.

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