

Bidding Strategy for a Wind-Battery System Using a Hybrid Stochastic Optimization-Deep Learning Method

Problem Description

Wind energy is becoming increasingly common in the US electricity supply. In US electricity markets, wind power producers (WPPs) submit generation offers in the day-ahead (DA) bidding stage, 12-36 hours ahead of scheduled power delivery. However, the forecast error at this horizon may be up to 20% of the wind farm's capacity [1]. This causes reliability issues for system operators. Also, WPPs may have to pay large penalties in the real-time (RT) market for failing to deliver the cleared DA offer.

Battery energy storage systems (BESSs) can be used to compensate for wind power forecast errors. During hours with high wind generation, the BESS is charged. Then, if the WPP is at risk of defaulting on its cleared DA offer, the BESS is discharged. This allows the WPP to provide its entire cleared DA offer through a combination of wind power and stored energy and reduces the risk of paying large RT penalties.

The goal of this research is to develop a strategy to strategically charge and discharge an on-site BESS, such that the BESS can be discharged during hours when the WPP has a high risk of default. It addresses the following key challenges:

- 1) Can deep learning improve the hybrid system operation compared to current state-of-the-art methods such as stochastic optimization (SO)?
- 2) Can the likelihood of default on the WPP's cleared DA offer be modeled and incorporated into the BESS control strategy?

References:

- 1) B.M. Hodge, E. Ela, and M. Milligan, "The Distribution of Wind Power Forecast Errors from Operational Systems", in Proc. 10th Int. Workshop on Large-Scale Integration of Wind Power into Power Syst., Aarhaus, Denmark, Oct. 2011.
- 2) ERCOT Market [Online]. Available: https://www.ercot.com/mktinfo/prices.
- 3) Draxl, C., B.M. Hodge, A. Clifton, and J. McCaa. 2015. "The Wind Integration National Dataset (WIND) Toolkit." Applied Energy 151: 355366.
- 4) K. Mongird, V. Viswanathan, J. Alam, C. Vartanian, V. Sprenkle, and R. Baxter, "2020 Grid Energy Storage Technology Cost and Performance Assessment," p. 117, 2020.
- 5) M. Elmahallawy, T. Elfouly, A. Alquani. A.M. Massoud, "A Comprehensive Review of Lithium-Ion Batteries Modeling, and State of Health and Remaining Useful Lifetime Prediction," IEEE Access, vol. 10, pp. 119040-119070, 2022, doi: 10.1109/ACCESS.2022.3221137.

First, the likelihood of default on the WPP's cleared DA offer is calculated. For an 80 MW WPP without a BESS, the wind offers of 10,000 hours are simulated. Then, market price data [2] is used to find the cleared offers, and real wind generation data [3] is used to determine whether a default occurred. The DA offers are binned and the number of defaults per bin is calculated. The resulting histogram is plotted and normalized, and a Weibull distribution is fitted to model the probability of default on the WPP's cleared DA offer, as shown in Fig. 1.

The goal of the optimization problem is to maximize the WPP's profit:

 $Profit = \sum_{i=1}^{n} \sum_{i=1}^{n} \pi_{\omega} [\lambda_{\omega t}^{DA}(DA Wind Offer - BESS Charge +$

This model is solved using SO. The problem is optimized for multiple scenarios of prices and wind power (ω) and for one day at a time (t). The expected DA/RT electricity prices are $\lambda_{\omega t}^{DA}/\lambda_{\omega t}^{RT}$. The Conditional Value at Risk (CVAR) is a risk management measure which gives the profit in the 5% least profitable scenarios. We assume that the BESS operation must be scheduled in the DA stage.

Afterward, a twin-delayed deep deterministic policy gradient (TD3) agent is used to re-optimize the BESS strategy. Fig. 2 shows the state (information the agent receives), action, and reward. The purpose of the TD3 algorithm is to incorporate the likelihood of default into the BESS strategy. The reward maximizes profit while minimizing defaults and keeping the BESS state-of-charge (SOC) in the safe range (20-98%).



DA offer.

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Methodology

BESS Discharge) + $\lambda_{\omega t}^{RT}$ (Actual Wind – DA Wind Offer) +

 $\lambda_{\omega t}^{RT}(-BESS \ Charge + BESS \ Discharge) + CVAR$





Fig. 2: TD3 state, action, and reward.

Results

The proposed method is tested on an 80 MW wind farm with a 20 MWh BESS. The BESS efficiency is 92.74% [4] and the maximum charge/discharge rate is 4 MW. The model is trained on 700 days using data from [2]-[3] and tested on 100 days. The CVAR weight is 0.01, which indicates mild risk aversion.



Fig. 3: Profit (left axis) and average difference in profit (right axis) for days with typical (top) and large (bottom) RT default penalties.

Table I: Profit for test days.			
Method	Wind	BESS	Total
SO:	\$2,366,300	-\$97,259	\$2,269,100
SO-TD3:	\$2,401,100	-\$120,400	\$2,280,700

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Conclusions

Using the SO-TD3 method increases profit compared to the SO method. This is because the likelihood of default on the cleared DA offer is incorporated into the TD3 strategy, allowing the WPP to avoid defaults during hours with high RT prices (Fig. 3). The SO-TD3 method also reduces the number of hours when the BESS discharges to its minimum SOC and prevents charging/discharging by large amounts (Fig. 4). These improvements will extend the battery lifetime, resulting in long-term cost savings [5].

Future work may include using the BESS to provide system reserves, incorporating the BESS health into the model, and testing the model for different likelihood of default distributions.



Fig. 4: BESS SOC for days with typical (top) and large (bottom) RT default penalties.

Table II: Frequency of BESS SOC < 21%.

Method	Num. Hours
SO:	365
SO-TD3:	24



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