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MPC for Reducing Energy Storage Requirement of Wind Power Systems

Chiao-Ting Li, Huei Peng, and Jing Sun

Abstract—**This paper discusses using the battery energy storage system (BESS) to mitigate wind power intermittency, so that wind power can be dispatchable on an hourly basis like fossil fuel power plants. In particular, model predictive control (MPC) is used to control the charge and discharge of BESS to compensate for wind power forecast errors and minimize operation costs to the wind farm owner. A ramp rate penalty on wind power scheduling is included in the optimization to make the optimal control trajectory smoother, while the performance is kept intact. Numerical simulations with a one-year long wind power dataset show that MPC controller is much more effective in reducing the operation cost to the wind farm owner than the heuristic control algorithm or conventional reserves, in that BESS with a much smaller capacity will be suffice to achieve the same cost reduction.**

I. Introduction

Wind power has been one of the most fast-growing new electricity generating capacities in in the U.S. [1], and, in 2010, wind power is the third largest renewable energy source after biomass and hydroelectric power [2]. While wind power has been touted as a free, clean, and sustainable energy source, it poses new challenges to the electricity wholesale market and grid operators, in that wind power outputs are intermittent, which may increase demands on reserves [3] in order to mitigate large deviations in frequency and voltage on the grid. Various studies have reported that costs of integrating wind power on the electric grid can be as high as \$12/MWh, although is often below \$5/MWh [4], meaning that not only the installation but also the operation of wind power plants is not free after all.

Since the intermittency in wind power can cause reliability problems and increase operation costs, studies have proposed to use energy storage systems to smooth wind power outputs and reduce variations. Although various technologies are considered as the energy storage system [5], the following discussion focuses on the battery energy storage system (BESS). Depending on the different time scales of interest, BESS can be designed and controlled to defer upgrades, achieve price arbitrage, or support reserves [6, 7]; consequently, methodologies for sizing the capacity of BESS and associated control algorithms for energy management differ. Various studies for sizing BESS to accommodate intermittent renewable energy exist in the literature, including maximizing the annual revenue by dynamic programming [8], minimizing costs of battery system installation and reserve dispatch by stochastic linear programming [9], using the artificial neural network as control strategies to keep the error of hour-ahead predictions below 4% for 90% of the time [10], using Discrete Fourier Transform to decompose forecast errors and quantify imbalances to be compensated by the energy storage system [11], conducting Monte-Carlo simulations to access the minimum storage requirement based on the degree of risk that the power producer choses to be exposed to [12], and conducting detailed dc-bus voltage simulations to find the minimum storage capacity to meet voltage regulation requirement [13]. A common theme can be identified from the diverse BESS sizing strategies, namely, methodologies focusing on shorter time scale dynamics, such as voltage and frequency regulation, generally lead to BESS with smaller capacities and methodologies focusing longer time scale objectives, such as price arbitrage, result in BESS with larger capacities. Other studies concerning only control algorithms for BESS and not sizing include adopting rule-based control algorithms to charge the battery when wind power exceeds a certain threshold [14], using droop control or PI-control algorithms to regulate voltage and/or frequency [15, 16], formulating optimizations in linear programming or stochastic programming for price arbitrage [17, 18], using model predictive control (MPC) to track battery state of charge (SOC) and to smooth wind power output [19-21] or to minimize operation costs [22].

This paper discusses the control of BESS to provide reserves to mitigate wind power intermittency, so that wind power can be dispatchable on the hourly basis like fossil fuel power plants. In particular, MPC will be used to control the charge and discharge of BESS to compensate for wind forecast errors and reduce operation costs to the wind farm owner. MPC is chosen as the control algorithm because meteorologists now can provide forecasts of wind power outputs up to several hours ahead of time [23, 24], and such information of future predictions can be incorporated in the framework of MPC to improve performances. In addition, MPC can help to enforce constraints on battery SOC in future time steps, so that BESS with a tiny capacity may be used. This paper also discusses the sizing of BESS for mitigating wind power intermittency. Simulation results show that the MPC controller is much more effective in reducing the operation cost to the wind farm owner than the heuristic control algorithm or conventional reserves, in that BESS with a much smaller capacity will be suffice for MPC to achieve the same cost reduction.

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The remainder of this paper is organized as follows: Section II explains models for describing the stochastic wind power outputs and battery dynamics; Section III presents different means for mitigating wind power intermittency, one of which is to adopt MCP to control BESS; and lastly, Section IV provides concluding remarks.

II. Modeling

Several models are developed to describe the stochastic wind generation and the battery state of charge dynamics.

A. Wind Power

The intermittency of wind power can be described by the probability distribution. A wind farm with an 800 MW nameplate capacity in eastern Michigan is chosen from the Eastern Wind Dataset of the National Renewable Energy Laboratory (NREL) [25], and Figure 1 shows a one-week long snapshot of the forecast and actual wind power outputs of this wind farm. The whole year-long data is used to extract the conditional probability distribution, denoted as $\mathbb{P}(w_a|w_f)$, which represents the (stochastic) actual wind generation (w_a) under a given forecast (w_f), shown in Figure 2. The peak value of each distribution is close to the forecast value, w_f, implying that the forecast is generally good. $\mathbb{P}(w_a|w_f)$ is then used to derive the reserve requirement ($R_{w,rqd}$) and wind power deficit (w_{short}) by Eqs. (1) and (2). The assumptions behind Eqs. (1) and (2) are that wind over-production can always be curtailed and reserves need to be scheduled to cover 95% of under-production [26].

$$R_{w,rqd}(w_f, w_s) = [w_s - \mathbb{F}^{-1}(0.05)]^+ \tag{1}$$

$$w_{short}(w_f, w_s) = [w_s - w_a]^+ \tag{2}$$

where both $R_{w,rqd}$ and w_{short} are functions of w_f and w_s. w_s is the scheduling of wind power, which is a control variable to be detailed in Section III. $\mathbb{F}$ is the cumulative probability distribution function of $\mathbb{P}(w_a|w_f)$, and $\mathbb{F}^{-1}$ is the inverse of $\mathbb{F}$. Then, $\mathbb{F}^{-1}(0.05)$ is the guaranteed wind power generation for 95% of time. Figure 3 shows the example of $\mathbb{F}$ at w_f = 400MW, and its inverse is found to be 58MW. This can be interpreted as follows: when the forecast is at 50% of the nameplate capacity, the actual wind output will be at least 7% of the nameplate capacity for 95% of time; then, Eq. (1) quantifies how much reserves need to be *scheduled* when the wind farm owner decides to schedule wind power higher than

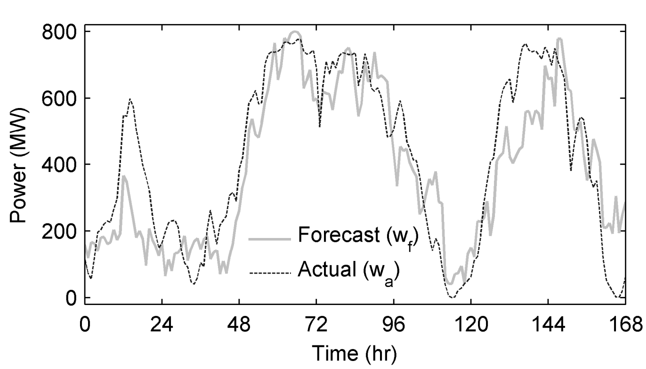

Figure 1. One-week long snapshot of the forecast and actual wind power outputs of an 800MW wind farm.

7% of the nameplate capacity, and Eq. (2) quantifies how many reserves will be *dispatched*. Both the reserve scheduling and reserve dispatch matter because they induce costs to the wind farm owner. The plus sign (+) in both Eqs. (1) and (2) indicates the truncation of negative values.

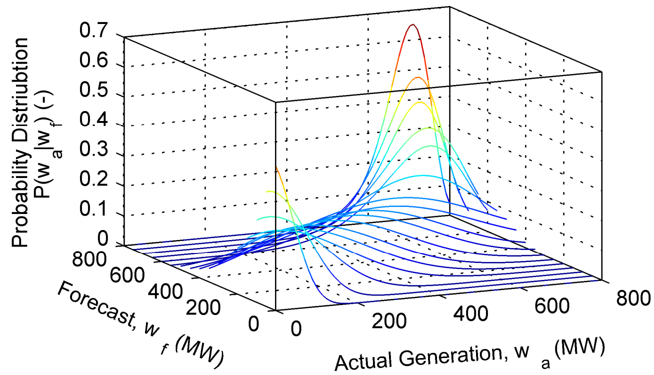

Figure 2. The conditional probability distributions, $\mathbb{P}(w_a|w_f)$ [26].

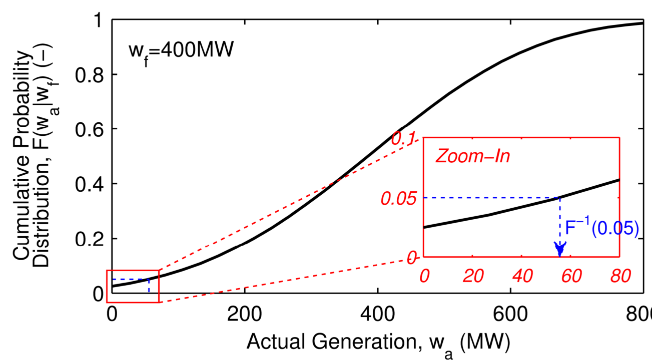

Figure 3. The cumulative probability distributions, $\mathbb{F}(w_a|w_f)$, at w_f = 400MW.

B. Battery

The dynamics of the battery state of charge (SOC) is governed by Eq. (3), with the assumptions that efficiencies of both charge and discharge are perfect, and responses of both charge and discharge are instantaneously fast.

$$SOC_{k+1} = SOC_k - (P_{batt} \cdot \Delta k)/Q \tag{3}$$

where P_{batt} is the battery discharge power, the time step, Δk, is 1 hour, and Q is the battery capacity.

Since the focus of this paper is to make wind power dispatchable on an hourly basis, the role of BESS is to supply hourly-long reserves. Assuming that the remaining energy content in the battery can be discharged in one hour, one can derive the power limits for charge and discharge based on the level of SOC. Figure 4 shows the derived power limits as functions of SOC. Then, it can be understood that BESS with a larger capacity will have larger discharge and charge power limits. For example, an 800 MWh BESS will have the discharge limit as 800MW at full SOC, whereas a 200MWh BESS will have the discharge limit only as 200MW at full SOC. The power limits saturate at ±800MW because the wind surplus and deficit will never exceed the nameplate capacity. Note that these limits are imposed so that it is guaranteed that BESS can cover wind power surplus or deficit for at least one hour before the next scheduling update happens, and these limits are not based on physical limitations of battery chemistry and power electronics. It is further assumed that the wind power deficit exceeding the battery discharge limit must be backed up by conventional reserves, and the wind surplus exceeding the battery charge limit will be curtailed. The former induces additional costs on the wind farm owner and the latter reduces revenues. Thus, it is crucial to control the battery SOC, so that the BESS can compensate for wind forecast errors as much as possible.

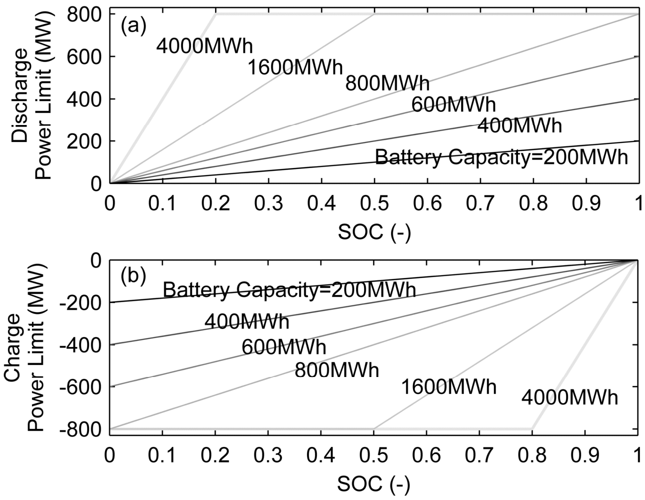

Figure 4. Power limits of battery. Subplot (a): discharge; (b): charge.

III. Mitigating Wind Power Intermittency

Figure 5 depicts how differently BESS and conventional reserves mitigate wind power intermittency. In both cases, instead of inserting wind power as a negative load on the grid, the wind farm owner is assumed to take actions (deciding the level of wind power scheduling) to isolate the power grid from fluctuations in the actual wind power outputs. Figure 5-(a) shows that, with conventional reserves, conservative control actions (i.e., scheduling wind power lower than the actual wind output) lead to wind curtailment and aggressive control actions lead to dispatching conventional reserves, both of which hurt the wind farm owner's revenue. Figure 5-(b) shows that, with BESS, a conservative (aggressive) control action implies charging (discharging) the battery, and, as long as the battery SOC can be controlled within an appropriate window, there is no need to curtail wind power or dispatch conventional reserves.

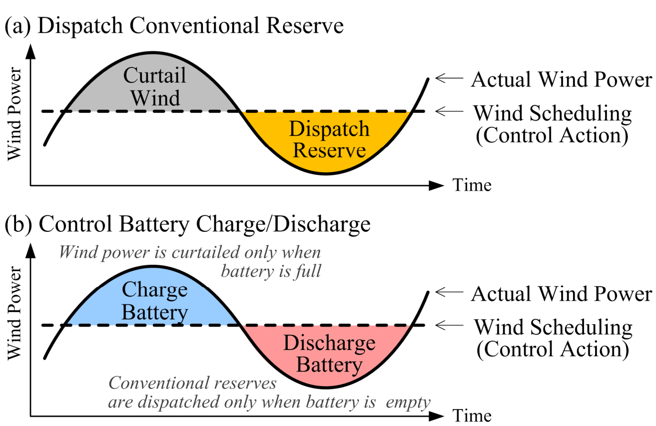

Figure 5. Two different ways to mitigate wind power intermittency.

To quantify the effectiveness of BESS over conventional reserves for mitigating wind intermittency, the operation cost to the wind farm owner are evaluated. In addition, BESS with different battery capacities are also investigated to understand how big battery needs to be to compensate for wind forecast errors and secure revenues to the wind farm owner.

A. Mitigating Wind Intermittency by Conventional Reserve

When using conventional reserves to mitigate wind intermittency, the wind farm owner solves the instantaneous optimization problem shown in Eq. (4) every hour to find the optimal wind power scheduling that minimizes the total hourly cost to the wind farm owner. The four terms in Eq. (4) are: 1) the revenue of selling wind power to the grid, 2) the expense of scheduling conventional reserves, 3) the *expected* expense of dispatching conventional reserves when wind under-production occurs, and 4) the cost of ramping service incurred when wind power scheduling fluctuates between adjacent hours. As mentioned in Section II-A, wind over-production is assumed to be curtailed and reserves need to cover only under-production, so the second and third terms in Eq. (4) take values defined in Eq. (1) and (2).

$$\min_{u_k}\left\{-C_1\cdot u_k + C_2\cdot R_{\mathrm{w,rqd}} + C_3\cdot \mathbf{E}\{w_{\mathrm{short}}\} + C_4\cdot|u_k-u_{k-1}|\right\} \quad (4)$$

where the control variable, u_k, is the wind scheduling (w_s) in hour k. The coefficients C_1, C_2, C_3, and C_4 are the unit price of electricity generation, reserve scheduling, reserve dispatch, and ramping services in the wholesale market, each of which takes the value defined in Eq. (5) based on statistics in [27] and [28].

$$C_1 = 1;\quad C_2 = 1.03;\quad C_3 = 1;\quad C_4 = 30/55 \quad (5)$$

Figure 6 shows the optimal wind power scheduling in a one-week long time window (the black trajectory), which indicates that the wind power scheduling is conservative (i.e., much lower than the forecast) for most of the time because the wind farm owner tries to avoid paying for conventional reserves. The conservative wind scheduling leads to high wind curtailment; the one-year long simulation shows that more than 60% of wind power outputs are curtailed.

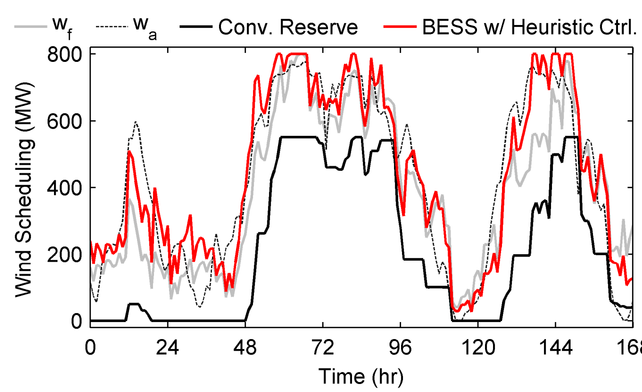

Figure 6. Wind power scheduling with conventional reserves and BESS. (BESS capacity: 4,000MWh)

B. Mitigating Wind Intermittency by BESS with a Heuristic Control Algorithm

To use BESS to compensate for wind power intermittency, a control algorithm is needed to regulate the battery SOC, and a heuristic control algorithm based on the current wind forecast and battery SOC is designed for this purpose. The heuristic algorithm is shown in Eq. (6).

$$u = w_s = w_f \cdot SF(SOC) \tag{6}$$

where *SF* is a scaling factor varying with respect to battery SOC. Figure 7 shows two sets of scaling factors; the blue line means that the wind farm owner adopts a simple-minded strategy which uses the wind forecast directly as the control without manipulation; whereas the red line means that the wind farm owner is concerned about the battery SOC and will schedule wind power at half of the forecast when SOC is at zero and at twice of the forecast when SOC is at one. Once the wind scheduling is known, the battery discharge power can be computed using Eq. (7) to update the battery SOC.

$$P_{batt} = u - w_a = w_s - w_a \tag{7}$$

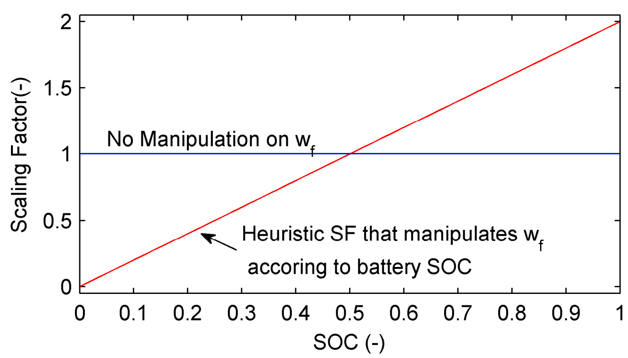

Figure 7. Scaling factor for the heuristic control algorithm.

Simulation results using a 4,000MWh BESS with the heuristic control algorithm to mitigate wind power intermittency are shown Figure 6 (the red trajectory). Compared to the optimal scheduling with conventional reserves (the black trajectory), the heuristic control algorithm is more oscillatory and less conservative; hence, the wind curtailment is reduced significantly, down to 0.6%. However, to achieve zero wind curtailment, the battery capacity needs to be 20 times the wind farm nameplate capacity (16,000MWh) according to an exhaustive search over a wide range of BESS capacity.

The heuristic control using only the current wind forecast to control BESS shows promising results in reducing wind curtailment, which inspires us to use MPC to design more sophisticated control algorithms that can better utilize multi-step-ahead predictions to improve performances and reduce the requirement on battery capacity. The MPC control algorithm is presented in the next section.

C. MPC Controller for BESS

Generally speaking, MPC is based on the solution of an on-line optimal control problem where a receding horizon approach is utilized, in which, for a given current state, an open-loop optimal control problem is solved over some future interval, taking into account current and future constraints and/or predictions. The first value in the optimal control sequence will be implemented. The procedure is then repeated in the next time step using a new updated state.

In this paper, the MPC controller for wind power scheduling with BESS uses the objective function in Eq. (8). This objective function is designed to be comparable (although not identical) to that in Eq. (4), in that the revenue of selling wind power to the grid, the expense of scheduling conventional reserves, the expense of dispatching conventional reserves, and the expense of ramping services are included.

$$\min_{\boldsymbol{u}} \Big\{ \sum_{i=k}^{k+N-1} \big[-C_1 \cdot u_i + C_2 \cdot R(u_i, x_i, \hat{w}_i) + C_3 \cdot \mathbf{E}\{r(u_i, x_i, \hat{w}_i)\} + C_4 \cdot |u_i - u_{i-1}| \big] \Big\} \tag{8}$$

where the control, u, is again the wind scheduling (w_s), the state, x, is the battery SOC, the prediction, $\hat{w}$, is the wind forecast (w_f), and x_{ref} is the desired SOC. R is the scheduling of conventional reserve, and r is the expected dispatch of conventional reserve, both of which are functions of u, x, and $\hat{w}$, as defined in Eqs. (9) and (10).

$$R = \left[R_{w,rqd} - P_{dis,lmt} \right]^+ \tag{9}$$

$$r = \left[w_{short} - P_{dis,lmt} \right]^+ \tag{10}$$

Eqs. (9) and (10) imply that using the BESS is preferred over dispatching conventional reserves because the latter induces costs. Furthermore, in addition to BESS, Eq. (8) keeps conventional reserves as an option for mitigating wind intermittency; thus, it is guaranteed that feasible optimal solution(s) exist. The optimization will just reduce to that in Eq. (4) in the worst case scenario when the battery is fully charged ($P_{chg,lmt} = 0$) or completely depleted ($P_{dis,lmt} = 0$).

Several constraints on the state and control are imposed, including Eqs. (3) and (7) on the state dynamics, and Eqs. (11)-(13) in below for lower and upper bounds on the state and control variables.

$$0 \le x \le 1 \tag{11}$$

$$0 \le u \le U \tag{12}$$

$$P_{chg,lmt} \le P_{batt} \le P_{dis,lmt} \tag{13}$$

where U is the upper bound for the control and takes the value of the nameplate capacity of the wind farm (800MW), $P_{chg,lmt}$ and $P_{dis,lmt}$ are the power limits of battery charge and discharge (as shown in Figure 4). The time horizon of the optimization is chosen to be 4 hours long because the 4-hour-ahead wind forecast is readily available in the NREL wind dataset [25].

Figure 8 shows the result of implementing the MPC controller (the green trajectory) with a 1,600MWh BESS. Compared to Figure 6, MPC outperforms both the conventional reserves and the heuristic algorithm, in that MPC achieves smooth wind power scheduling and zero wind curtailment with a smaller battery. The much better performance of MPC comes from the fact that the future information (wind forecasts) is factored in during the decision making, so that MPC may still schedule wind power aggressively when the battery SOC is low. Shown in Figure 9, it is found that MPC allows the battery SOC to swing in a wider range, which implies that the buffer provided by the BESS is better utilized.

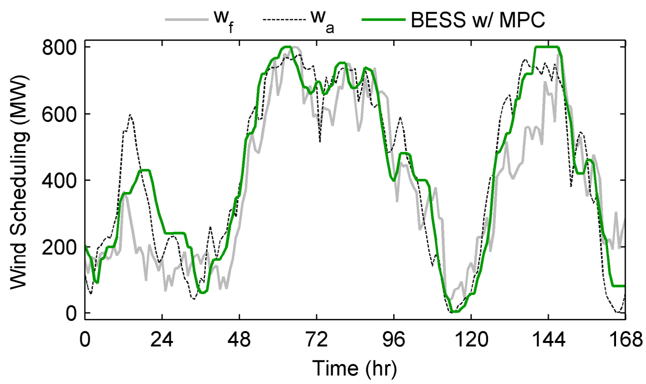

Figure 8. Implementation of MPC (BESS capacity: 1,600MWh).

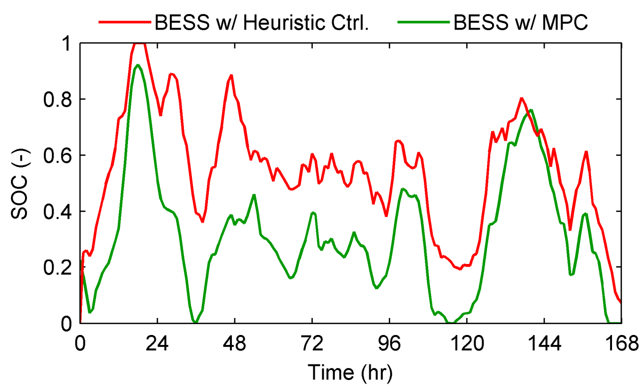

Figure 9. Battery SOC trajectories (BESS capacity: 1,600MWh).

D. Comparison of Different Control Algorithms for BESS

Figure 10 compares total annual revenues (the converse of total operation costs) of the wind farm owner when adopting different sizes of BESS and control algorithms. The revenue of using conventional reserves is also included, and the number indicates that, if wind farm owners procure reserves from only conventional (fossil fuel) sources, it will be very difficult for wind power to obtain grid parity. Furthermore, it is found that the MPC controller is, in general, better than the heuristic algorithm; in particular, the MPC controller is significantly better when the BESS capacity is small. In fact, it is found that the BESS has a 600MWh capacity (75% of the wind farm nameplate capacity) is sufficient to cover most of the wind intermittency and can secure a revenue similar to those when much larger BESS are used, whereas the heuristic algorithm requires a 800MWh BESS to secure the same revenue. The performance gap between MPC and the heuristic algorithm reduces when the BESS capacity gets bigger, which is consistent with the intuition that a bigger battery will be more tolerant in wind forecast errors and less intelligent control algorithms.

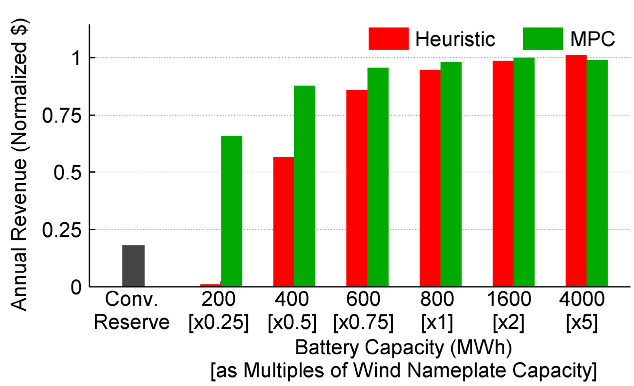

Figure 10. Annual revenue of the wind farm owner.

The annual wind power curtailment can be another metric to evaluate how well the wind intermittency is mitigated. Figure 11 summarizes the annual wind power curtailment, and there is no doubt that using BESS can reduce wind curtailment compared to using conventional reserves. For example, BESS with a capacity merely one-quarter of the wind farm nameplate capacity outperforms conventional reserves significantly. In addition, the heuristic control algorithm, surprisingly, has lower wind power curtailment than MPC when the BESS capacity is very small (the 200MWh case). However, this does not quarantine a better revenue. Based on the optimization formulation in Eq. (8), it is indeed more profitable to play save and be conservative in scheduling wind power when having a very small BESS although it leads to higher wind curtailment. Furthermore, as the BESS capacity increases, MPC becomes more effective the heuristic algorithm to reduce wind curtailment. More specifically, MPC only need a 1,600MWh BESS to reach zero wind curtailment, whereas the heuristic control algorithm requires a BESS larger than 16,000MWh to do so.

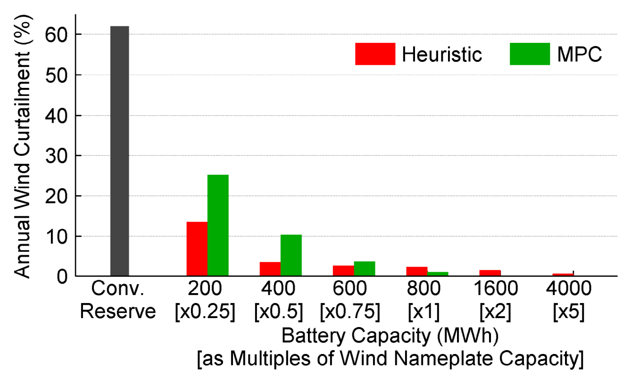

Figure 11. Annual Wind Cu

IV. Conclusion

This paper proposes using MPC to control the charge and discharge of battery energy storage system (BESS) for mitigating wind power intermittency, so that wind power can be dispatchable on the hourly basis like fossil fuel power plants. The MPC controller is designed based on the optimization that minimizes operation costs for the wind farm owner where multiple-step wind forecasts (predictions) are included. The optimization is formulated in a way that the MPC results can be compared to conventional reserves and the heuristic algorithm that uses only the wind forecast at the current time step. Simulation results show that MPC can achieves both smooth wind power scheduling and low wind curtailment. In addition, the BESS capacity only needs to be 75% of the wind farm nameplate capacity to cover most of the wind intermittency and to secure the wind farm owner's revenue.

Several aspects demand further investigation include: 1) incorporating more a sophisticated battery model to better represent power limitations, efficiencies of charge and discharge events, and state of health; 2) conduct more comprehensive analysis on costs, including not only operation but also installation, to provide more insight into the feasibility of deploying BESS on the electricity grid.

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