Grid Optimization of Shared Energy Storage Among Wind Farms Based On Wind Forecasting

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Abstract—Energy storage is crucial for source-side renewable energy power plants for enhancing output stability and reducing mismatch between power generation and demand. However, installing large size energy storage systems for renewable energy plants may not be economic, due to high capital cost and ever-increasing human resources and maintenance cost. As a result, in this paper, a shared energy storage system among multiple wind farms is proposed to address this energy management challenge. A state-of-the-art wind power forecasting method with ensemble numerical weather prediction models is used to optimally determine the size of a shared energy storage system (ESS). A number of scenarios are performed to optimize and explore the energy storage size under different economic and storage resource sharing circumstances. The performance of ESS, namely the net revenue of power plants, is explored subject to ESS size and operating constraints of wind farms and power systems. Results of a case study show that sharing of energy storage among multiple wind farms and lower cost of storage progressively enhance the economic benefits of using storage to mitigate over-production/under-forecasting (thus curtailment) and under-production/over-forecasting scenarios.

Index Terms—shared energy storage, wind energy, optimization, wind forecasting.

I. Introduction

To efficiently manage the uncertainty and variability of wind energy, energy storage has been extensively proposed to balance the power output and demand. Current main energy storage technologies for power systems include lithium-ion battery, ultracapacitors, flywheel, and redox flow battery.

Energy storage has been widely used in power system operations for different applications. For example, Wang *et al.* [1] used energy storage to meet the requirement of economic dispatch between the distribution network operators and customers. Gouveia *et al.* [2] explored the benefits of using energy storage in demand response and grid integration of electric vehicles. On the other hand, utilities also adopt the energy storage into their power generations, with the aim to provide stable and reliable power generation, and to minimize the operation and interrupted-load cost. Some researchers have also integrated the storage technology into renewable energy systems such as solar [3] and wind [4]. However, most of existing research focuses on using energy storage in the demand side, or wind/solar generation side within a microgrid. Thus, full benefits of using energy storage in power system operations are still not well studied, especially the

benefits to renewable power plants owners. To bridge the gap in using energy storage with renewable generators, this paper develops an innovative shared energy storage strategy among wind farms. This shared energy storage concept seeks to maximize the benefits of energy storage, especially for wind farm owners. The shared energy storage system could help wind farm owners to manage the wind power forecasting errors at different timescales, thereby reducing the wind curtailment or penalty loss during the unit commitment process [5]. Thus, wind forecasting accuracy plays an important role in determining the optimal size, charging, and discharging schedules of the shared energy storage system. Wind power forecasting methods can be generally divided into three categories [6], [7]: (i) physical models that are usually based on numerical weather prediction (NWP) models; (ii) statistical methods, most of which are intelligent algorithms based on data-driven approaches; and (iii) hybrid physical and statistical models.

In this paper, a wind power forecasting improvement (WFIP) system that consists of an ensemble of high-resolution rapid-update NWP models is adopted to generate day-ahead wind power forecasts. The forecasts are used to determine the energy storage size by considering both over-forecasting and under-forecasting scenarios. The remaining of the paper is organized as follows. Section II briefly describes the WFIP framework and the novel energy storage sharing concept. Section III provides energy storage sizing case studies with differing numbers of wind farms. Section IV provides concluding remarks and future work.

II. Methodology

A. WFIP Framework

The WFIP forecasting system consists of an ensemble of high-resolution rapid-update numerical weather prediction (NWP) models [8]. Each of these ensemble members incorporates a variety of model configurations, physics parameterizations, and data assimilation techniques. The purpose of integrating all of these ensemble members into one system is to construct an optimized composite forecast, which is expected to be able to predict forecast uncertainty and assess the relative performance of different modeling approaches. Figure 1 shows the overall framework of the wind power forecasting system. The WFIP ensemble members include [8], [9]:

i. The National Oceanic and Atmospheric Administration's 3-km High-Resolution Rapid Refresh model, updated hourly;

ii. Nine NWP models updated every 2 hours on a 5-km grid:

- Three configurations of the Advanced Regional Prediction System
- Three configurations of the Weather Research and Forecasting model
- Three configurations of the Mesoscale Atmospheric Simulations System

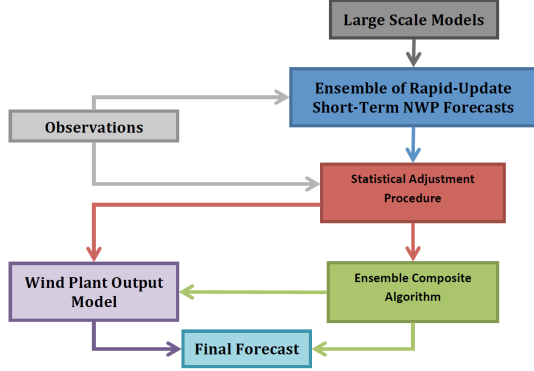iii. An Advanced Regional Prediction System model updated every 6 hours on a 2-km grid.

Fig. 1: Overall framework of the wind forecasting system [8]

B. Energy Storage Simulations

An energy storage simulation is introduced here to model the expected energy exchange between individual wind farms and the (grid-scale) battery storage unit. Energy exchange is invoked when either of the following two scenarios occur: 1) "*wind farm→storage*": the energy production of the wind farm is greater than that forecasted (*overproduction*); or 2) "*storage→wind farm*": the energy production of the wind farm is lower than that forecasted (*underproduction*). The simulation operates on an hourly scale, i.e., considers the averaged energy production over 1 hour periods, while using days-ahead forecasting estimates in II-A.

The following set of assumptions are made to formulate the *grid-scale-storage/wind-farm* energy exchange simulation:

1) Underproduction and overproduction are both penalized financially (by the utility), thereby encouraging wind farms to reduce the gap between their forecasted and actual (hourly) energy production.
2) We use the Tesla Battery Pack as our reference system for grid-scale energy storage [10]. The maximum charging and discharging rate of the battery storage unit is proportional to the battery capacity. More specifically, the maximum discharging rate is assumed to be 40% of the battery capacity, and the maximum charging rate is assumed to be 20% of the battery capacity (based on the reference system).
3) When the battery storage unit is shared by multiple wind farms, energy exchanges are distributed or curtailed proportionately among the participating wind farms. For example, if the stored energy or maximum discharging

rate (of the storage unit) is lower than the net energy-transfer request by all underproducing wind farms, a factor η is applied to all requests, such that all energy exchanges are curtailed by $1 - \eta$ (further explained in Eqn. 8 to 11).

4) Since the objective of the simulation here is to perform a design study, real-time constraints are not considered; all energy exchanges are aggregated over the hourly period, where the constraints due to energy availability in the storage or maximum charging/discharging rates are effective on an hourly scale.

The net energy exchange, $R^i(t)$, requested by the i-th wind farm in any hourly interval t can expressed as:

$$R^i(t) = e^i(t) = y_h^i(t) - y_{fi}^i(t) \tag{1}$$

In the above equation, $e^i(t)$ is forecasting error, $y_h^i(t)$ is actual energy production, and $y_f^i(t)$ is forecasted energy production in that hourly interval. $(R^i(t) > 0)$ indicates overproduction, and hence "*wind farm→storage*" or storage charging request is invoked; and $(R^i(t) < 0)$ indicates underproduction, and hence "*storage→wind farm*" or storage discharging request is invoked.

When m different wind farms are sharing the storage, the total charging and discharging (energy exchange) requests are given by:

$$Q_{ch}(t) = \sum_{i=1}^{m} (R^i(t) : R^i(t) > 0) \tag{2}$$

$$Q_{dis}(t) = \sum_{j=1}^{m} (R^j(t) : R^j(t) < 0) \tag{3}$$

where $Q_{ch}(t)$ and $Q_{dis}(t)$ are respectively the energy transferred to (charging state) and from (discharging state) the storage unit.

However, it might not be possible to meet the total charging or discharging request due to the available energy in the storage or the maximum charging/discharging rate capacity of the storage system. Hence, the actual energy transferred to/from the battery in a hourly interval t needs to satisfy certain constraints.

The actual energy transferred to (charging state of) the battery in the hourly interval t, $\bar{Q}_{ch}(t)$, is thus determined by Eqn. 4 to 7.

$$\eta_{ch}^1(t) = \frac{(E_b - Q_b(t-1)) * E_{ch}}{Q_{ch}(t)} \tag{4}$$

$$\eta_{ch}^2(t) = \frac{(R_{ch}^{max}) * E_{ch}}{Q_{ch}(t)} \tag{5}$$

$$\eta_{ch}(t) = min[1, \eta_{ch}^1(t), \eta_{ch}^2(t)] \tag{6}$$

$$\bar{Q}_{ch}(t) = Q_{ch}(t) * \eta_{ch}(t) \tag{7}$$

In the above equations, the coefficient $\eta_{ch}^1(t)$ shows the fraction of the charging request that can be met subject to the energy capacity, E_b, of the storage, and the coefficient $\eta_{ch}^2(t)$ shows the fraction of the charging request that can be

met subject to the maximum charging rate, $R_{ch}^{max} = 0.4 * E_b$ (based on our assumed battery pack [10]), of the storage; $Q_b(t-1)$ is the stored energy state of the battery at the end of the previous time interval; E_{ch} is the charging efficiency of the battery storage unit. So, the actual allowed charging fraction, $\eta_{ch}(t)$,is subject to two constraints, and takes the smallest value among $\eta_{ch}^1(t)$, $\eta_{ch}^2(t)$ and 1.

The actual energy transferred from (discharging state of) the battery in the hourly interval t, $\bar{Q}_{dis}(t)$, is thus determined by Eqns. 8 to 11.

$$\eta_{dis}^1(t) = \frac{(Q_b(t-1))}{Q_{dis}(t) * E_{dis}} \tag{8}$$

$$\eta_{dis}^2(t) = \frac{(R_{dis}^{max}) * E_{dis}}{Q_{dis}(t)} \tag{9}$$

$$\eta_{dis}(t) = min[1, \eta_{dis}^1(t), \eta_{dis}^2(t)] \tag{10}$$

$$\bar{Q}_{dis}(t) = Q_{dis}(t) * \eta_{dis}(t) \tag{11}$$

Similar to the charging formulation, in the above equations, $\eta_{dis}^1(t)$ shows the fraction of the discharging request that can be met subject to the energy capacity, E_b, of the storage, and the coefficient $\eta_{dis}^2(t)$ shows the fraction of the discharging request that can be met subject to the maximum discharging rate, $R_{dis}^{max} = 0.2 * E_b$ (based on our assumed battery pack [10]), of the storage; $Q_b(t-1)$ is the stored energy state of the battery at the end of the previous time interval; E_{dis} is the discharging efficiency of the battery storage unit. So, the actual allowed discharging fraction, $\eta_{dis}(t)$, is subject to two constraints, and takes the smallest value among $\eta_{dis}^1(t)$, $\eta_{dis}^2(t)$ and 1.

Therefore, the net hourly energy exchange requests ($Q_{ch}(t)$ or $Q_{dis}(t)$), made by m wind farms, represent the energy output gap between the forecasted and the actual generation with no storage. With the shared storage in place, this energy output gap reduces to: $Q_{ch}(t) - \bar{Q}_{ch}(t)$ or $Q_{dis}(t) - \bar{Q}_{dis}(t)$. An illustration of the thus simulated energy output gap for a selected set of 10 wind farms from Texas, over a period of about a week, is given in Fig. 2; this figure exhibits the reduction of the gap accomplished with a shared storage of 2,000 MWh.

C. Optimization Study

A preliminary optimization study is performed here to investigate suitable storage sizing under different economic and storage resource sharing scenarios. The objective of this study is two-fold: 1) to explore the potential benefits of sharing energy storage resources across multiple wind farms; and 2) to explore the sensitivity of the economic benefits of energy storage to the penalties associated with over-/under-production. A straight-forward idealized economic model is used for these explorations. A cost-to-benefit study is enabled by: considering the installed storage resource as an investment, and the penalties (underproduction) and curtailment (overproduction) mitigated via storage as an earning or revenue savings. Given the focus of this paper, the following assumptions are made in this regard:
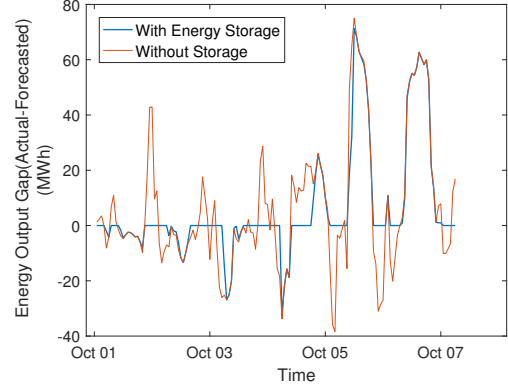

Fig. 2: Hourly energy output gap (actual - forecasted) of 10 wind farms with/without shared storage (of 2,000MWh)

1) The lifetime of a wind farm T_f is 25 years. Cost of electricity from source-to-grid (C_e), cost of storage (C_b), and penalty cost for underproduction (C_p) does not change during the lifetime of the wind farm.

2) Since the capacity of battery-based energy storage decreases over time ($\sim$10% per year for the reference system), the same storage unit may not be used over the entire lifetime of the wind farm. This, along with the consideration of potential maintenance, repair, replacement costs of energy storage units, calls for an annualized measure of the net cost of energy storage. Hence, the unit cost of energy storage (C_b) is expressed in terms of average annual cost per kWh, i.e., with units $/kWh*Yr.

3) The economic estimations are made based on forecasting data and actual production data from a single year, both of which are assumed to hold for the entire 25 year lifetime of the wind farm.

With these assumptions, using the energy storage as a buffer − that closes the gap between forecasted and actual energy supplied by the source − the revenue savings can be directly computed from the energy exchanges between the storage unit and the wind farm(s). For example, the revenue savings (C_{over}) attributed to mitigating *overproduction* is given by:

$$C_{over} = \sum_{t=1}^{8760} \bar{Q}_{ch}(t)C_e \tag{12}$$

where C_e can be perceived as the (at source) cost of energy (in $/kWh) that would otherwise have been curtailed.

The revenue savings (C_{under}) attributed to mitigating underproduction is given by:

$$C_{under} = \sum_{t=1}^{8760} \bar{Q}_{dis}(t)C_p \tag{13}$$

where C_p can be perceived as the penalty (in $/kWh) imposed (by the utility) on underproduction of the wind farm, with respect to their day-ahead forecasts.

The net economic gain over the wind farm's lifetime, attributed to using storage as the buffer (that reduces the forecast/actual energy output gap), is given by:

$$C = 25 \times (C_{over} + C_{under} - E_b C_b) \quad (14)$$

where $E_b C_b$ is the average annual cost of the installed energy storage. The optimal storage sizing problem can then be readily defined as:

$$E_b^* = \max_{E_b} \ f(E_b, C_b, C_p, C_e, S) = C \quad (15)$$

where the set S contains the forecasted and actual energy output (time series) data of the m wind farms sharing the energy storage.

Since, Eqn. 15 presents a straightforward univariate, unconstrained, and non-linear programming problem, which is also observably convex (see Figs. 3a and 4a); hence, a typical line search technique, the bisection method, is used to determine the optimal storage sizing. A relative tolerance of 2.5e-03 (which translates to about 5 MWh) is used to terminate the line search. It was also found that the variation of the net economic gain with energy storage sizing is unimodal (as observed from the illustrations provided in Section III-A); this observation further supported the feasibility of using a typical line search technique. Section III-A provides description of the case studies performed to explore the optimum sizing, the associated economic benefits, and how both are impacted by: i) the number of wind farms participating in the storage sharing, ii) the unit cost of battery storage, iii) the penalty cost of underproduction, and iv) the cost of curtailment.

III. CASE STUDY

A. Results and Discussion

We consider 25 wind farms, taken from the Electric Reliability Council of Texas (ECORT) site list. This list pertains to day-ahead wind power forecasting. The historical hourly average power generation from these sites from October 1, 2011 to September 21, 2012 (i.e., about a year) is used to verify the accuracy of WFIP method, develop the energy storage simulations, and perform the case studies described in this section. Further information regarding these wind farms can be found in [8].

The simulation and optimization (described in the previous section) are implemented using MATLAB. Case studies are performed to explore how sharing the energy storage across (increasing number of) multiple wind farms and the cost of energy storage impact the storage sizing decisions and the associated revenue savings. The case study settings are summarized in Table I.

Figure 3(a) show the variation of (normalized) revenue savings with increasing storage capacity installation, when differing numbers of wind farms (from 1 to 25) share the energy storage. Revenue savings (Eqn. 14) are normalized by the net installed capacity of the wind farms considered. It can be observed that beyond certain capacity the revenue savings become negative, meaning that securing greater storage is

financially infeasible. Figure 3(b) show that while the optimal storage sizing varies (somewhat) quadratically with increasing number of farms that share the resource, the corresponding (optimal) normalized revenue increases linearly with increasing number of participating wind farms. It should be noted that the wind farms considered here are not homogenous (have different installed capacities). The linear growth in normalized revenue savings (million $/kW-installed) does point towards the benefit of sharing energy storage resources.

Figure 4(a) show the variation of the (normalized) revenue savings of 10 selected wind farms with increasing (shared) storage capacity installation, for different (average annual) pricing of energy storage (in $/kWh.Yr). The upper (ceiling) of $40/kWh.Yr is close to the cost of (currently available) reference system. It can be observed that the revenue savings become increasingly sensitive to the cost of energy storage. Further, it can be seen from Fig. 4(b) that the optimal storage sizing and corresponding revenue savings vary quadratically with the cost of storage, with the former being more sensitive to the storage cost. These observations are also indicative of the increasing benefits of energy storage once (average annual) storage costs decrease below ∼$20/kWh.Yr.

Battery (energy storage) technologies are advancing progressively, with the projected cost of energy storage expected to decrease by 70% by 2030 (as forecasted by a World Energy Council report [11]). From the findings in this paper, it is readily observable that source-side energy storage could become not only a viable but an economically rewarding option for wind farms. Such economic viability/ benefits could be further enhanced through sharing of energy storage assets across multiple wind farms.

IV. CONCLUSION

In this paper, a shared energy storage strategy among multiple wind farms based on wind power forecasting was developed for grid optimization. A state-of-the-art wind power forecasting method with ensemble numerical weather prediction models was used to optimally determine the size of a shared energy storage system (ESS). The case study's on optimal storage sizing and related revenue savings showed that optimized revenue savings (attributed to mitigating penalty and curtailment with energy storage) increases linearly with number of wind farms sharing the storage and decreases quadratically with the (annual average) cost of energy storage. The corresponding optimal battery sizing or capacity respectively shows a quadratic variation with both number of participating wind farms (increasing) and cost of storage (decreasing). An important direction is thus evident from these findings: expected reduction in costs of energy storage in the future will increase the viability of supply side energy storage adoption; and sharing of energy storage assets between multiple renewable energy plants should be carefully investigated as a unique approach to accelerate this viability and benefits of adopting storage-based grid optimization. In this context, it is important to note that physically such storage systems remain scalable due to their modular design, and mathematically, the

TABLE I: Case study's: Revenue savings and optimum storage sizing under different sharing and economic scenarios

Case no.	No. of wind farms	Annual storage cost ($/kWh.Yr)	Curtailment Cost ($/kWh)	Underproduction Penalty ($/kWh)
Case-1	1 - 25	20	0.08	0.02
Case-2	10	8 - 40	0.08	0.02

(a) Variation of normalized revenue savings with storage capacity

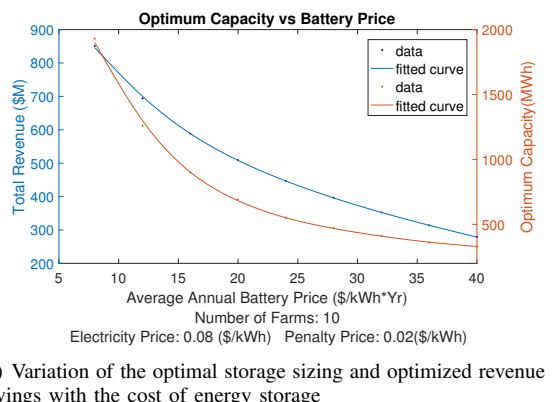(b) Variation of the optimal storage sizing and revenue savings with number of wind farms sharing the storage
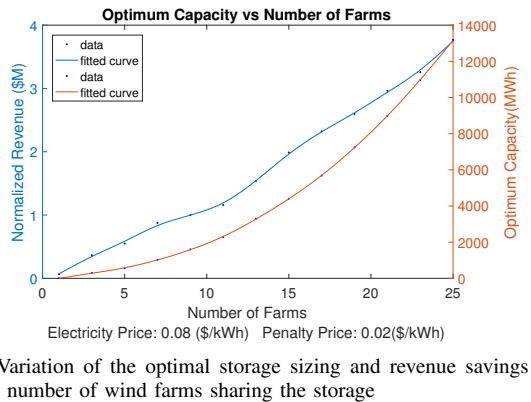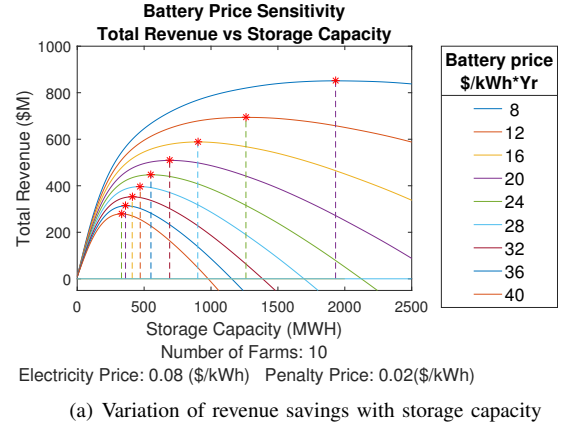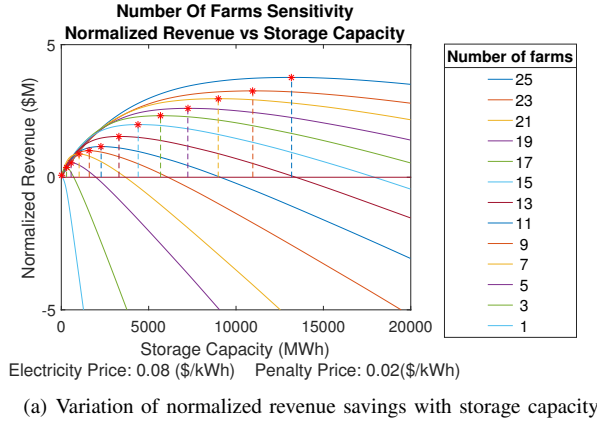
Fig. 3: Impact of number of wind farms sharing energy storage

(a) Variation of revenue savings with storage capacity

(b) Variation of the optimal storage sizing and optimized revenue savings with the cost of energy storage

Fig. 4: Impact of cost of energy storage

scale does not significantly impact the approach to optimal sizing. However, the actual/simulated operation of a shared storage could become increasingly constrained and complex with greater number of participating wind farms sharing the storage, and with considerations of the nature (cooperative vs. competitive/auctioned) of the sharing scheme − these important directions of future investigations will likely facilitate greater interest in and understanding of the benefits of supply side grid-scale storage.

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