Technical and economic value of utility-scale wind-storage hybrid power plants

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Technical and economic value of utility-scale wind-storage hybrid power plants

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***Abstract*—The potential technical benefits of wind-storage hybrids, mainly arbitrage, imbalance reduction, and frequency support, are convincing enough to launch demonstration projects. However, a quantitative analysis of these benefits, including economic considerations, is lacking. The aim of this study is to establish at what costs such technical benefits can be achieved, and whether developers reap sufficient economic advantage to make the development of such hybrid plants attractive. A wind-storage power plant is simulated for arbitrage, imbalance revenue maximization, and secondary frequency support using the Internal Rate of Return as a parameter to measure the economic performance. It is found that, for a wind-farm developer, deploying batteries just for arbitrage and/or imbalance revenue maximization does not improve profitability at current levels of battery costs. However, there is a strong economic incentive for a wind farm developer to deploy batteries to participate in the secondary frequency market.**

Keywords: Hybrid power plant, wind power, battery energy storage, energy markets, ancillary services

I. Introduction

The role played by renewables in meeting the decarbonization goals cannot be emphasized more. A large number of wind and solar farms are being deployed owing to the widespread presence of the resource and maturity of the technology. However, as the penetration of wind and solar energy in the energy system increases, the integration poses a major challenge. As wind and solar depend on the availability of the resource, which is uncontrollable, they are intermittent in supply. This leads to various issues related to high balancing reserves and their associated integration costs (upto $5/MWh, shown by W. Katzenstein and J. Apt [1]), inefficient use of the grid infrastructure, frequency fluctuations, forecasting errors, etc. Adding storage can alleviate some of these issues. Deploying storage at a generator or a system operator level can reduce power imbalances from forecasting errors, enable energy arbitrage, provide frequency support, flexibility of generation, congestion relief, etc. As mentioned in a report of IRENA [2], of all the storage types, battery storage (especially Li-ion) makes up the largest share of total installed storage capacity, mainly due to its rapidly declining costs. This research explicitly focuses on co-located wind-battery storage Hybrid Power Plants (HPP).

Adding storage to wind has seen a lot of positive light in the past few years in the form of both demonstration and commercially operational projects. As discussed by Wind Europe [3], about 400 MW of co-located wind-storage hybrids have already been made operational (or announced) globally, where battery is mainly used as the storage source. Petersen *et al.* [4] discuss the learnings from the hybrid power plant projects of Vestas. For instance, the Lem Koer project demonstrated the advantages of coupling wind with storage in the form of reduced penalties, reduced ramp rates, capabilities in providing ancillary services, etc. Klonari *et al.* [5] study the existing HPP around the world, of which most systems are a combination of wind and storage, and identify drivers and barriers followed by some probable policy changes that could be implemented. The authors identified capacity firming to be the most widely used functionality of a hybrid power plant, and they also state that the business case of having HPP, from a developer point of view, is still under development. An important conclusion drawn by the authors was that these utility-scale HPP are not fully rewarded by the current market incentives.

Extensive research has been carried out on detailed modelling of wind-storage HPP where the enhanced value of adding storage is discussed. B. Cheng and W. Powell [6] optimized the battery for arbitrage and frequency control using multi-scale dynamic programming. However, the main objective was to develop and display the functionality of the algorithm. Heredia *et al.* [7] developed a stochastic model to find the optimal operation of a wind-battery system in the day-ahead, intraday, and the secondary reserve market taking into account all the uncertainties. The authors concluded that profits from the reserve market exceed that of the day-ahead market, and the increase in total profit was about 10%, compared to the wind-only case, when the battery was used for the day-ahead and imbalance market. Similar results w.r.t revenue increase were reported by Kaushik *et al.* [8] where the optimal operation of a wind-battery system in the Danish market is shown. Bolado *et al.* [9] also analyze the value of storage in performing arbitrage including price forecasting using Artificial Neural Networks.

Overall, an analysis including storage costs is missing, which is also the case for many studies where the focus is the efficacy of the model/algorithm. Sioshansi [10] examined the use of storage for arbitrage. The author reported that the current costs of storage technologies may not justify this use. This conclusion is very relevant to this research as the aim here is to provide a preliminary techno-economic analysis in order to identify the use cases where adding storage would be economically beneficial to the developer:

'The objective is to establish, by quantitative analysis, the scenarios under which wind-battery HPP could be economically beneficial from a generator point of view.'

These economic benefits will differ from one country to another, but the scope of this study is limited to the electricity market of the Netherlands. The paper first describes a generic bidding and real-time operation model for wind-storage HPP in this market. The strategies for two specific storage applications, namely the energy market and the imbalance market (ancillary services), are then described. Finally, the case study definition is provided and the results for the two storage applications are discussed.

II. Generic Model

This section discusses the general modelling approach used in this research.

A. Model overview

A complete setup of the model is shown in Figure 1. The red lines represent flow of information while the black lines represent actual power flow. The bidding block uses forecasts from the wind and the market to make predictions, day-ahead, and place the bid in the spot or imbalance market, depending on the application of storage. In real-time, the controller uses actual market information along with actual wind generation and battery energy status to make opportunistic decisions. The controller decides whether to send the wind power as it is to the grid, whether to charge the battery using wind, whether to discharge the battery along with wind, whether to take in energy from the grid, etc. This is indicated by the red signal that operates the switch.

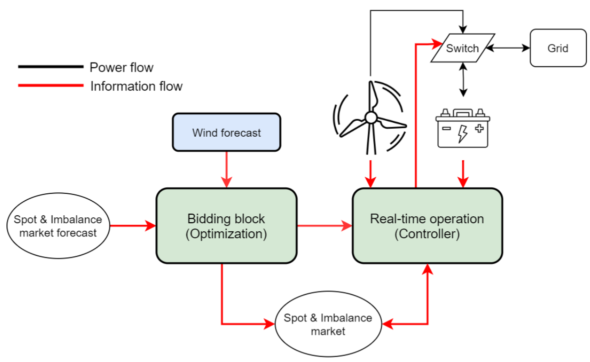

Fig. 1. Generic model of wind-storage HPP investigated

In this research, it is assumed that the bidding optimizer has perfect knowledge of both the spot and the imbalance market while optimizing the bids day-ahead. It is known that this is not completely realistic but it sets the best economic case for wind-storage HPP. The objective is to have a preliminary model to find out applications that are economically profitable for storage which can then form as a basis for future detailed studies.

B. Wind

For wind speeds below cut-in, the power is zero while for wind speeds between rated and cut-out, the turbine operates at its rated power (P_{rated}). For all the wind speed values between cut-in and rated, the power produced can be determined using equation (1), where v is the wind speed, C_p is the power coefficient, A_{rotor} is the area of the rotor, and η_{dt} is the drivetrain efficiency.

$$P(v) = 0.5 \cdot C_p(v) \cdot \rho \cdot A_{rotor} \cdot v^3 \cdot \eta_{dt} \qquad (1)$$

To simulate the wind forecasts, an error signal is imposed on the actual wind generation. This error signal is based on the nationwide error between wind forecasts and actual generation. The Netherlands being a small country (by area), it is assumed that the forecasting errors made by all the wind generators are in the same direction. The histogram of forecasting errors normalized w.r.t the nationwide installed capacity is shown in Figure 2. The data used is open-source, provided by the European Network of Transmission System Operators for Electricity (ENTSO-E) [11].

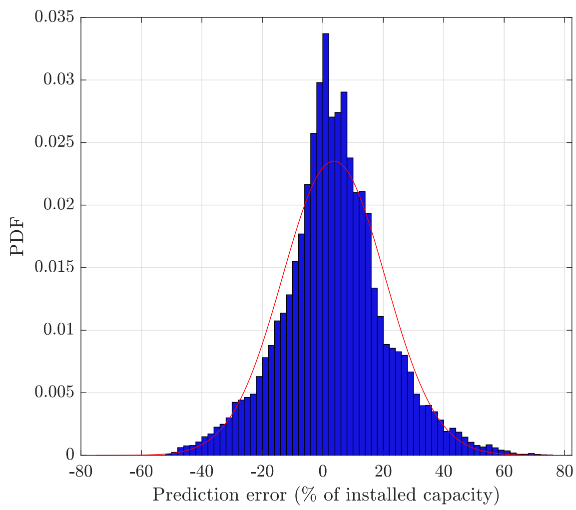

Fig. 2. Offshore wind forecasting error (as a function of installed wind capacity) in 2019

C. Storage

In this paper, storage is coupled with wind for two different applications. For each use case, a different objective function is implemented, and will be stated in the next chapter while the constraints implemented are nearly the same other than the case specific constraints.

The battery energy level (E_{batt}) and the normalized State Of Charge (SOC) at any given time stamp are given by equation (2) & equation (3), respectively.

$$E_{batt}(t) = E_{batt}(t-1) + x_{cha}(t-1) \cdot \eta_b - x_{dis}(t-1) \cdot \frac{1}{\eta_b} \quad (2)$$

where x_{cha} and x_{dis} is the power with which the battery is being charged and discharged, respectively. Also, depending on charging or discharging, the efficiency term (η_b) is adjusted.

$$SOC(t) = \frac{E_{batt}(t)}{E_{cap}} \quad (3)$$

where E_{cap} is the total battery energy capacity.

D. Market

This study deals with two different markets, namely the spot market and the imbalance market. In the bidding phase, it is assumed that the controller has perfect forecast of both markets. Using this information along with the wind forecast, it places a bid. The bid being placed in the spot market or the imbalance market depends on the storage application. If the battery is used for arbitrage, it places the bid in the spot market while if the battery is used to provide ancillary services, it places a bid in the imbalance market. In real-time, using the real-time wind generation, battery energy state, and market information (which, due to the assumption, is the same as the forecast), the controller decides how to re-iterate the operation of the hybrid plant so as to maximize the revenue.

E. Bidding & real-time operation

The bidding block uses an optimization algorithm so as to optimize the operation of the hybrid plant to maximize the revenue while in real-time, the controller simply re-iterates the operation based on actual information of the market, wind generation, and battery energy state. These two blocks can be best explained for the given storage application and will be discussed in detail in the next chapter.

F. Economic figure of merit

The figure of merit chosen in this study to evaluate the economic feasibility of a particular configuration is the Internal Rate of Return (IRR). It is the rate at which the Net Present Value (NPV) of a project is zero, as shown in equation (4), where Cf_n represents the cash flows over the years and C_0 represents the initial investment. Thus, by comparing the IRR values of different cases, the better performing case can be identified.

$$0 = NPV = \sum_{n=1}^{N} \frac{Cf_n}{(1+IRR)^n} - C_0 \quad (4)$$

The IRR values for different wind-storage configurations have been normalized with the wind-only case. In this case, an IRR lower than 1 does not mean the business case has negative value, or isn't profitable. It simply means that the case is not as profitable as the wind-only case.

III. Storage applications

The purpose is to use storage to enhance the value of an existing wind farm by tapping into two different possible revenue streams. To guide the reader with some nomenclature, a generator participating in the day-ahead energy market is referred to as the Balance Responsible Party (BRP) while a generator providing frequency restoration services to the grid operator, by placing bids in the imbalance market, is referred to as the Balancing Service Provider (BSP). It should be noted that an asset can also be registered both as a BRP and as a BSP so as to provide services in multiple markets.

A. Energy arbitrage with imbalance revenue maximization

Energy arbitrage is a concept wherein the instants of production and consumption are separated. To maximize the revenue, battery storage can be used to store some energy when the day-ahead market prices are low and sell energy when the market prices are high. Also, as the developers place their bids day-ahead, the prediction of overall farm output needs to be done 12-36 hours in advance, which could result in a significant deviation between forecasted power and actual power generation. This is where battery storage could add value by maximizing the revenue from imbalances. Here, the wind-storage plant is solely acting like a BRP, placing bids in the spot market.

To place the bids in the day-ahead market, a simplex optimization algorithm is used to determine the combined power of wind and batteries in order to maximize the revenue. The bids are then placed in the market by 12 pm on the previous day. The most basic form of optimization for arbitrage using storage can be summarized by equation (5), where x is the design vector, consisting of battery charge (x_{cha}) and discharge (x_{dis}) values (adjusted w.r.t efficiency), λ_{DAM} is the day-ahead market price, 96 is the number of Imbalance Settlement Periods (ISPs) in a day, and P_{cap} is the maximum battery power capacity, depending on the duration and battery energy capacity. As the bidding happens day-ahead, the bidding optimizer would have no knowledge of the battery state in real-time, and hence the final value of the actual and forecasted SOC is forced to be equal. This final battery SOC value is then used as the initial SOC for the new optimization to be carried out for the next day.

$$\begin{aligned} \max_{x} \quad & f(x) = \sum_{t=1}^{96} (x_{dis}(t) - x_{cha}(t)) \cdot \lambda_{DAM}(t) \\ \text{s.t.} \quad & 0 < x_{dis}(t) < P_{cap} \\ & 0 < x_{cha}(t) < P_{cap} \\ & 0.3 < SOC(t) < 1 \\ & SOC(t=97)_{act} = SOC(t=97)_{forc} \\ & SOC(t=97)_{D} = SOC(t=1)_{D+1} \end{aligned} \quad (5)$$

In real time, the actual wind generation, spot prices, and the imbalance price for every 15 mins (ISP) are checked. Based on the power deviations between wind generation and the placed bid (P_{diff}), and the price difference between imbalance and spot price (δ), a decision is made whether to re-iterate the battery operation or to stick to the original battery schedule.

For a situation where wind generation is higher than the bid volume ($P_{diff} > 0$):

- If $\delta > 0$, sell the excess to the imbalance market instead of charging the battery.
- If $\delta < 0$, charge the battery to minimize P_{diff} and if some imbalances still remain, sell to the imbalance market.

For a situation where wind generation is lower than the bid volume ($P_{diff} < 0$):

- If $\delta > 0$, discharge the battery to minimize P_{diff} and if some imbalances still remain, buy from the imbalance market.
- If $\delta < 0$, buy the deficit from the imbalance market instead of discharging the battery.

B. Ancillary services

Frequency regulation, voltage control, black-start capabilities, are some examples of ancillary services that can be provided by storage. The imbalance market in the Netherlands comprises of the primary, secondary, and tertiary frequency market. The primary frequency market responds to the real-time grid frequency, at a time resolution of one second, while the secondary frequency market operates at a time resolution of 15 minutes. In this paper, a preliminary analysis for the secondary frequency support market, also known as the automatic Frequency Restoration Reserve (aFRR) market, is performed. According to Tennet [12], the TSO of the Netherlands, the secondary frequency market is about thrice the size of the primary frequency market, which is also a reason why it was chosen.

For a contracted BSP in the aFRR market, there exists a capacity and an energy remuneration. The BSP bids a fixed capacity in the upward and downward direction for the entire day, day-ahead, for which it receives the capacity remuneration, and every time the BSP is activated in real time to resolve the imbalances in the system, it receives an energy remuneration as well. In this analysis, it is assumed that the wind side of the HPP acts as a BRP while the battery serves a dual purpose where it acts as a BSP and also tries to maximize the imbalance revenue, where the imbalances are due to the errors in the wind power prediction. It is assumed that the BSP has perfect knowledge of the imbalance market day-ahead. It is known that this assumption is not realistic but it sets the best possible economic case for battery storage. It is also assumed that the BSP is always activated hence receiving an energy payment for each Imbalance Settlement Period (ISP) along with the capacity payments.

Based on the perfect information assumption of the imbalance market, the aFRR optimizer decides the up and down bids to be placed in the market. The wind forecast is directly used to bid in the day-ahead market. The objective function is given by equation (6) and the optimization can be summarized by equation (7). The two variables x_{up} and x_d represent the capacity bid in the imbalance market in the upward direction (battery discharge) and downward direction (battery charge), respectively. The activation state of the bid is represented by two boolean vectors, β_{up} and β_d. The imbalance market in a state of up-regulation for a particular ISP would result in the β_{up} for that ISP being 1 and β_d being 0, and the reverse for down-regulation. The capacity remuneration can be determined by multiplying λ_{cap}, the capacity revenue in Euro/MW/hr, with the capacity offered (the same for 24 hours) while the energy remuneration can be obtained by multiplying the net energy delivered in a particular ISP and λ_{imb}, the imbalance market price. The division by 4 converts the power delivered to energy for a given ISP (15-min).

$$\begin{aligned} f(x) = (x_{up} + x_d) \cdot 24 \cdot \lambda_{cap} + \\ \sum_{t=1}^{96} (x_{up} \cdot \beta_{up}(t) - x_d \cdot \beta_d(t)) \cdot (\frac{1}{4}) \cdot \lambda_{imb}(t) \end{aligned} \tag{6}$$

$$\begin{aligned} \max_{x} \quad & f(x) \\ \text{s.t.} \quad & 0 < x_{dis}(t) < P_{cap} \\ & 0 < x_{cha}(t) < P_{cap} \\ & 0.3 < SOC(t) < 1 \\ & SOC(t = 97)_{act} = SOC(t = 97)_{forc} \\ & SOC(t = 97)_D = SOC(t = 1)_{D+1} \end{aligned} \tag{7}$$

In real time, depending on the actual wind generation and the imbalance situation in the country, the battery decides whether to mitigate the forecasting error in the wind generation or whether to settle it via the imbalance market. It should be noted that the battery mitigates the error only if doing so does not hamper the aFRR schedule of the battery for the rest of the day.

IV. Case study definition

This section discusses the general set of assumptions, and the wind and storage parameters used in this research.

A. Generic assumptions:

Some general assumptions that are adopted throughout the study are listed below:

- All studies are performed for the Netherlands.
- Wind speed, spot price, and imbalance price data have a temporal resolution of 15-min.
- Cesar observatory measurement data for the wind speeds are used.
- The data points are temporally correlated, and are from 2019.
- The study assumes utility-scale HPP.

B. Wind power

The system specifications used for the analysis are listed in Table I where P_{rated} is the rated power of the turbine and D_{rotor} is the rotor diameter.

TABLE I
Assumptions related to wind

	System assumptions	
Wind	Turbine P_{rated}	5 MW
	Turbine D_{rotor}	128 m
	Total installation costs	\$1870/kW

The Power coefficient (C_p) of the turbine used is based on the power curve of the Siemens Gamesa G128-5 turbine.

C. Storage

The system specific assumptions pertaining to storage are listed in Table II. A battery lifetime model has not been included in this analysis. The intent however is to carry out a preliminary analysis using the best possible conditions and identify if the use case has some potential value.

TABLE II
ASSUMPTIONS RELATED TO STORAGE

Storage assumptions	
Storage type	Li-ion
Duration	1,4 & 8 hour battery
Energy costs	\$ 165/kWh
Power costs	\$ 125-365/kWh (duration dependent)
Round-trip efficiency	90 %
SOC limits	0.3 - 1

V. Results & Discussion

This section discusses the economic value of wind-storage HPP, from a developer perspective, for the two described storage applications. For each storage application, a working example of the algorithm is shown first followed by the economic value of storage.

A. Energy arbitrage with imbalance revenue maximization

A plot displaying the behaviour of various parameters is shown in Figure 3. In the first subplot, the blue line is the wind power forecast while the red bars are the bids placed in the day-ahead market along with battery charge/discharge values, optimized to maximize the revenue. A value higher than the blue line indicates battery discharge, which can also be seen as a positive red peak in the third subplot. The blue line in the third subplot indicates the re-iterated battery operation taking into account real time wind generation and imbalance prices. The second subplot shows the prices in the spot and the imbalance market while the fourth plot shows the forecasted and actual battery SOC.

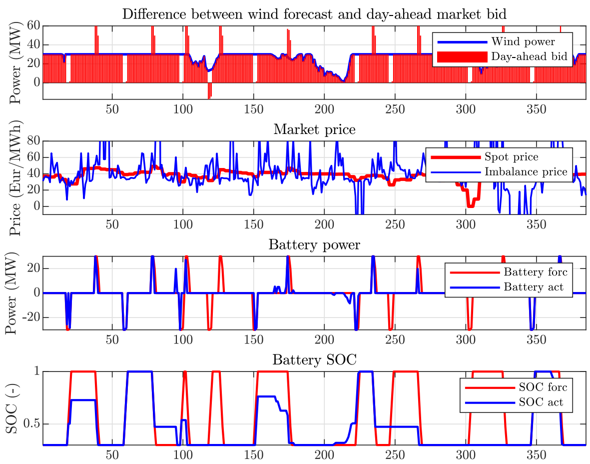

Fig. 3. Typical parameters plotted over time to illustrate the working of the algorithm for arbitrage along with imbalance revenue maximization

As an example, just before the 250^{th} time stamp, the bid indicates that the wind power charges the battery so as to discharge at a later point when the spot prices are higher. However, in real time, the controller observes that the imbalance prices are extremely high (as the country was in an overall deficit) which is why it chooses to ignore the original bid and instead sells the wind power directly in the imbalance market. In such a case, the battery state remains unchanged as seen by the flat blue line in the third subplot and the flat blue SOC line in the fourth subplot.

Figure 4 shows the increase in revenue, with the majority stemming from arbitrage, due to added battery storage. It should be noted that in the Netherlands, a developer is not charged a direct penalty for a deviation made from the bid value. As long as the deviation mitigates the system imbalance, the developer is rewarded. This is why even for the wind-only case, a forecasting error may be beneficial as long as it helps restoring the system imbalance. For instance, if a wind farm generator produces more than the forecast at a time when the country is in a deficit, the generator would receive the imbalance price (higher than the spot price) for the additional power generated.

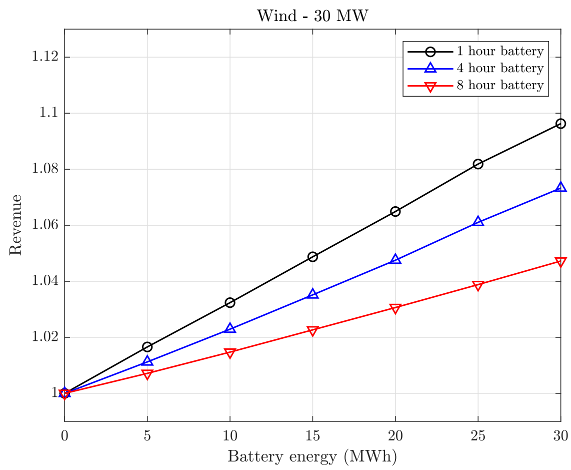

Fig. 4. Normalized increase in revenue due to storage

Similar results w.r.t revenue have been reported by Kaushik *et al.* [8] where the authors performed extensive simulations for the day-ahead market case including effects of battery lifetime, wind forecasts, and market forecasts on the revenue.

Figure 5 shows a complete picture of the economics of the system. When the battery costs are taken into account, the IRR drops compared to the wind-only case. This indicates that there is no added incentive for a wind farm developer to deploy storage for arbitrage along with imbalance revenue maximization.

It is estimated that the battery costs need to drop by about 50% in order for the arbitrage case to be more profitable than the wind-only case. Also, day-ahead market prices have a major influence on this result. With a higher share of renewables in the grid, there may be more margin for arbitrage resulting in an added value for storage.

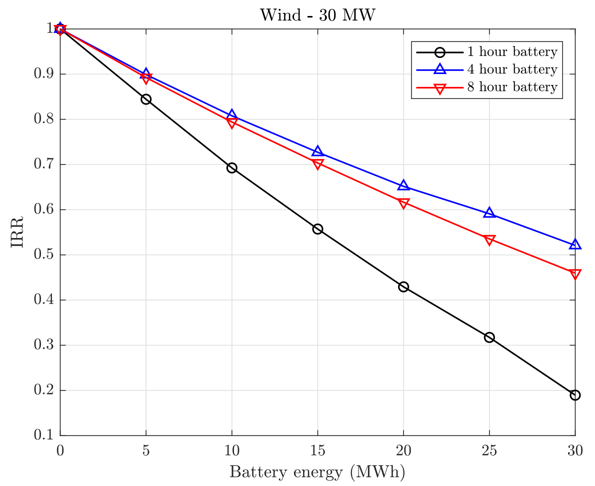

Fig. 5. Economics of a wind-storage system for arbitrage with imbalance revenue maximization

B. Ancillary services

A plot displaying the behaviour of various parameters is shown in Figure 6. The first subplot shows the capacity bids activated for a given day. A positive value indicates discharge (or power to be sold in the market) while a negative value indicates charge (or power to be bought from the market). It should be noted that all the charge bids need to have a constant capacity for a given day, and the same also holds for all the discharge bids. For some ISPs, the bidding optimizer does not place a bid (e.g. at time stamp 105). These rare instances correspond to a regulation state where the Transmission System Operator (TSO) does not activate any bids or a situation when both upward and downward bids are activated. The second subplot shows the difference between wind forecast and actual generation. The third subplot shows the forecasted SOC value (optimized for the aFRR market) and the actual SOC value (after iterations made to maximize imbalance revenue).

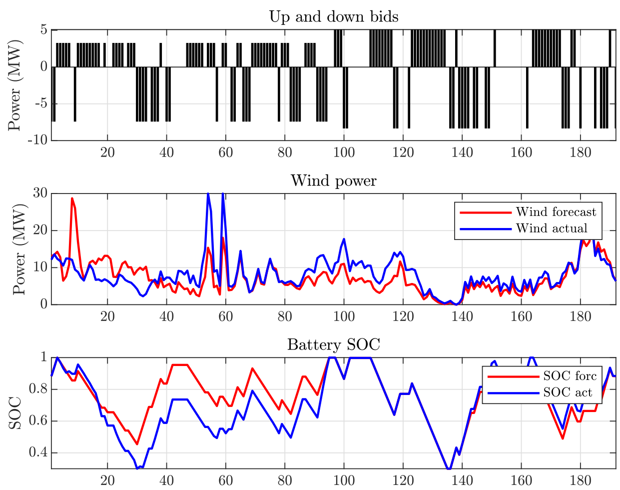

Fig. 6. Key parameters plotted over time illustrating the working of the aFRR algorithm

As an example, before the 20^{th} time stamp, the actual generation is lower than the forecasted value. At the same time, the battery had placed a positive bid (indicating a market need for up-regulation in the system). This is a situation where the imbalance prices are usually higher than the spot price and hence, the battery tries to minimize the fluctuation by discharging more than predicted (seen by the deviation between the blue and the red SOC curve). An example of the opposite effect can be seen at the 90^{th} time stamp, where the actual generation is higher than the forecast and the battery had placed a negative bid (indicating a need for down-regulation in the system). This is why the battery decides to charge (seen by the blue SOC curve ramping up quicker than the red SOC curve).

Figure 7 shows the complete economic scenario of this particular use case where it can be seen that under the assumption of perfect market information, participation in the aFRR markets is highly profitable for a wind-storage system.

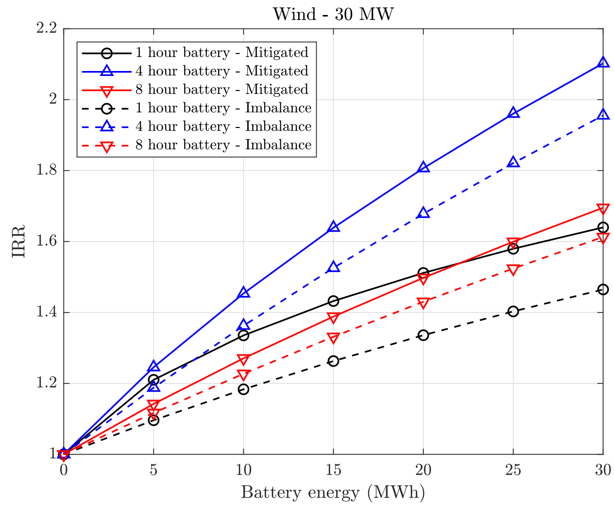

Fig. 7. Economics of a wind-storage system for the aFRR market with imbalance reduction

Due to the assumption of perfect imbalance market information, day-ahead, this case sets the upper bound to the profitability that can be achieved by using storage for contracted aFRR services. It is also observed that for the current battery costs, a 4-hour battery proves to be more beneficial than a 1-hour battery owing to the high battery power costs for a 1-hour battery with a marginal added benefit. The dashed lines represent the case where the battery is used only for bidding in the aFRR market while the solid lines represent the dual-use case where the battery is also used to maximize the imbalance revenue where the imbalances are generated from the wind forecasting errors.

VI. Conclusion

The analyses performed identified the value of adding storage to a wind power plant for two specific applications and recognized the economic benefit, if at all, to the developer. For wind-storage HPP, based on the above results and additional sensitivity studies, the following application-specific conclusions can be drawn:

A. *Arbitrage with imbalance revenue maximization*

- Adding a 1-hour battery for arbitrage and imbalance reduction, with an energy capacity roughly the size of the wind farm, can increase the revenue by about 10% compared to that of the wind-only case. However, in terms of IRR, a 4-hour battery has a better economic case.
- Extra revenue/value added by energy arbitrage is about three times the revenue generated by mitigating the imbalances. The overall combined value still does not result in a business case better than the wind-only system.
- A reduction of about 50% in battery costs would be required to make it economically attractive (compared to the wind-only case).

B. *Ancillary services*

- Using battery storage to bid in the aFRR market along with its use to mitigate the imbalances has a strong economic case.
- A positive business case for storage is due to the assumption of having perfect information of the imbalance market day-ahead. A more realistic case, when the BSP has little prior information of the imbalances, would reduce the added value by storage. The realization of this maximum potential is highly dependent on the state of the art market forecasting capabilities.

This preliminary research suggests that providing ancillary services is a more attractive economic case for adding battery storage to an existing wind plant than arbitrage. It also shows that using the battery for maximizing imbalance revenue where the imbalances result from wind forecasting errors, has a significant added value. However, for an accurate estimate of the IRR and the true economic potential, other factors like imperfect market knowledge, battery lifetime, grid connections costs, limited grid capacity, etc. must also be included in the analysis.

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