Optimal battery operation for revenue maximization of wind-storage hybrid power plant

Kaushik Das, Anatole Louis Theodore Philippe Grapperon, Poul E Sørensen, Anca D Hansen
Department of Wind Energy
Technical University of Denmark (DTU)
Risø, Denmark
kdas@dtu.dk

***Abstract*—In order to participate in energy market, variable renewable energy sources need to reduce the uncertainty of forecast errors. Inclusion of storage can be a viable option not only to minimize the penalties due to forecast uncertainties but also to maximize the revenue generation. This paper presents a decision framework for respecting the market constraints and maximise the revenues of a wind and storage power plant. Wind power and price forecast are used in convex optimisation algorithm for making day ahead decisions on battery operation. This day ahead optimisation results feed to an algorithm for operating in the balancing market. Several scenarios and case studies have been simulated to assess the value of storage for revenue maximization of a wind power plant. The results show that proposed algorithms can increase the revenue by more than 10% compared to the operation of wind power plant without battery.**

***Index Terms*—balancing market, battery storage, day-ahead optimisation, revenue maximization, spot market, wind power**

NOMENCLATURE

BESS	Battery Energy Storage System
HPP	Hybrid Power Plant
CET	Central European Time
CEST	Central European Summer Time
LSTM	Long Short Term Memory
SOC	State Of Charge
$\widehat{\lambda}^{spot}$	Forecasted spot price [€/MWh]
$\widehat{P}_t$	Day ahead power forecast [MW]
P_t^{spot}	Day ahead power bid [MWh]
P_{max}^{HPP}	Maximum power of the HPP [MW]
P_{max}^{BESS}	Maximum power of the BESS [MW]
P_t^{dis}	Discharging power from the BESS [MW]
P_t^{cha}	Charging power to the BESS [MW]
SOC_{min}	Minimum state of charge [MWh]
SOC_{max}	Maximum state of charge [MWh]
SOC_t	State of charge of the battery [MWh]
η_{leak}	Leakage loss of the BESS [MW/MWh/hour]
η_{dis}	Discharging loss of the BESS [MW/MW]
η_{cha}	Charging loss of the BESS [MW/MW]
$switch_t$	Binary variable for the charge and discharge
$\widehat{SOC}_{start}$	SOC estimated at the opening of the market
λ^{spot}	spot price [€/MWh]
C	Value associated to the remaining SOC at the end of the day $SOC_{t_{24}}$ (optional) [/MWh]
$SOC_{mismatch}$	mismatch between the SOC_{goal} and the $SOC_{t_{24}}$ (optional) [MWh]
SOC_{goal}	Goal state of charge for the end of the bidding period (optional) [MWh]

This work is done as part of Indo-Danish project "HYBRIDize" funded by Danish Innovationsfonden (IFD)

I. INTRODUCTION

Increasing concern for climate change, energy security as well as reducing prices for renewable generation technologies is leading to transition of traditional energy systems to renewable sources driven energy systems. Among the renewable generation sources, wind turbines and solar photovoltaics (PV) are most prevalent and economic generating sources. However, the challenges with these generations come from inherent variability of the natural resources. Until recently, most of the wind power plants (WPPs) have been developed either with feed-in-tariffs or power purchase agreements. However, in future WPPs need to participate in the energy markets for revenue generation. Addition of storage increases the dispatchability of the WPPs. Storage is particularly relevant for markets where power prices are zero correlated or negatively correlated with wind power productions such as Danish power market. Storage allows WPP to increase the revenue through flexibility and time shifting of the power production. Benefits of dispatchability and flexibility is further pronounced in wind, PV and storage based hybrid power plants (HPPs) [1]. When more and more renewables are integrated in the power systems, the possibility of curtailment also increases either from system security point of view or due to overproduction compared to load. Storage can also be useful in minimizing the spilling of excess energy, thereby reducing the loss of revenue for the power plant owner. Further, storage is helpful to reduce the impact of forecast error and thereby, reduce penalty due to imbalances. Power curtailment alongside with forecast error penalties reduce the profit of the renewable power plants. This paper develops a novel optimization for battery control to maximize revenue for a power plant from energy market. The methodology is general for WPP or PV power plant or an HPP. However, for simplicity and easy understanding, storage and wind based HPP is considered in this paper.

There has been many works in literature regarding usage of storage together with WPP for energy arbitrage. In [2], a battery energy storage system (BESS) is implemented in a large WPP to smoothen power output. This paper assumes that the forecast achieves to predict hourly average of the power. However, this method can't be applied for bidding in day ahead market. Yao et. al. [3] introduced a control scenario using two batteries such that the WPP is not connected to the grid but only to one battery. While the battery connected to the WPP is charging, the other battery is connected to the grid and is discharging. Using such scheme require massive investments in BESS. An approach for trading in the intraday market has been developed by Skajaa et. al. [4] and shows high complexity of such a method. Luo et. al. [5] and Li et. al. [6] developed control strategies for BESS based on forecast. Similar to [3], the dispatch implemented enforce that the battery is fully cycling and not following random fluctuations as in [2]. In [5], three power forecasts are generated and sorted as the optimistic, pessimistic and average forecasts. The output power is then set to either the optimistic when the battery is empty or to the pessimistic when the battery is charged. In [6], the approach is a little different but does not change fundamentally. In both of these cases, the HPP is allowed to reschedule its production after a certain time window without penalty. All these strategies are difficult to implement in the European market structure and often need to use large batteries and therefore very expensive solution [7]. Most importantly, all these studies although efficient in addressing wind variability often give too little interest in revenue optimisation in the electricity markets.

Crespo-Vazquez et. al. [8], [9], Gomes et. al. [10] and Pinson et. al. [11] focused in modelling the various electricity markets and ways to operate in it. In [8], [9], [11], much effort is put in refining forecasts using various techniques such as neural networks, stochastic analysis or multivariate fitting while in [10] a Monte Carlo approach is used to randomly generate scenarios from the original data. Based on these renewable generation and market forecasts, the bidding strategy is set through an optimisation algorithm often a linear optimisation with the objective of maximising the revenues. In [8], [9] and [10] even though the market design is really detailed there is a lack of consideration of the battery operation and cycles compared to the articles [3], [5], [6]. There is also a general lack of consideration for the operation over a full year with seasonal variation of price and wind power production.

The objective of this paper is to develop a novel algorithm for optimal operation of wind storage HPP. BESS control and optimisation strategy is developed for maximising revenue. The strategy involves an integrated bidding algorithm covering day ahead market and regulating period respecting the Danish market structure. Detailed studies are performed to assess the value and power to energy ratio of storage together with WPP.

This paper is structured as following. Section II describes the mathematical optimisation model for day-ahead bidding, balancing operation and revenue calculation. Section III simulates realistic scenarios, case studies and sensitivity analysis based on historical prices and wind power production. Section IV concludes the paper.

II. Optimisation model

The bids are submitted by HPP in the day-ahead spot market based on available weather forecast. Forecast error can often lead to high regulating costs. A first approach is to use a battery to try to smooth the forecast errors and reduce the regulating costs. Another approach to increase the revenue can be to use the flexibility of battery in order to take advantage of the highest electricity prices to produce more and charge it when the prices are low. This second approach brings up another uncertainty in terms of market price forecast. Therefore, battery charging and discharging strategy for minimizing day-ahead forecast error can be different from maximizing revenue from energy market. Additionally, WPP operator can try to minimize the day-ahead forecast error in intra-day and regulating markets when new forecasts are available, since the forecasts closer to real time operation are expected to have have lower error than day-ahead forecast. The operation can be divided in two parts - 'Day-ahead optimisation' and 'Balancing operation' as shown in Fig. 1. The revenue is calculated afterwards based on the day ahead bid, the power transmitted to the grid and the market prices.

A. Day-ahead Optimisation

The basic principle for optimisation in the spot market is to maximise the spot revenue according to the production and market forecast considering power plant production constraints (battery losses, maximum power, etc). The proposed algorithm optimises over a full day of 24 hours. The optimisation window starts at midnight CET/CEST and ends 24 hours later.

The algorithm is presented in the following equations:

$$\max \Pi_d^{spot} = \sum_{t \in T} (\widehat{\lambda}_t^{spot} \cdot P_t^{spot}) \quad (1)$$

subject to:

$$|P_t^{spot}| \leq P_{max}^{HPP} \quad \forall t \in [t_0, t_{23}] \quad (2)$$
$$P_t^{spot} = \widehat{P}_t^{res} + P_t^{dis} - P_t^{cha} \quad \forall t \in [t_0, t_{23}] \quad (3)$$
$$P_t^{dis} \leq P_{max}^{BESS} \cdot (1 - switch_t) \quad \forall t \in [t_0, t_{23}] \quad (4)$$
$$P_t^{cha} \leq P_{max}^{BESS} \cdot switch_t \quad \forall t \in [t_0, t_{23}] \quad (5)$$
$$0 \leq P_t^{dis} \quad \forall t \in [t_0, t_{23}] \quad (6)$$
$$0 \leq P_t^{cha} \quad \forall t \in [t_0, t_{23}] \quad (7)$$
$$SOC_{min} \leq SOC_t \leq SOC_{max} \quad \forall t \in [t_0, t_{23}] \quad (8)$$
$$SOC_t = \widehat{SOC}_{start} \quad t = t_0 \quad (9)$$
$$SOC_{t+1} = SOC_t \cdot (1 - \eta_{leak}) \quad (10)$$
$$+ P_t^{cha} \cdot \eta_{cha} \cdot \Delta t - \frac{P_t^{dis}}{\eta_{dis}} \cdot \Delta t \quad \forall t \in [t_0, t_{23}]$$

Binaries: $switch_t$

The objective function (1) is maximising spot revenue, Π_d^{spot} based on forecasted spot price, $\widehat{\lambda}_t^{spot}$ and day ahead

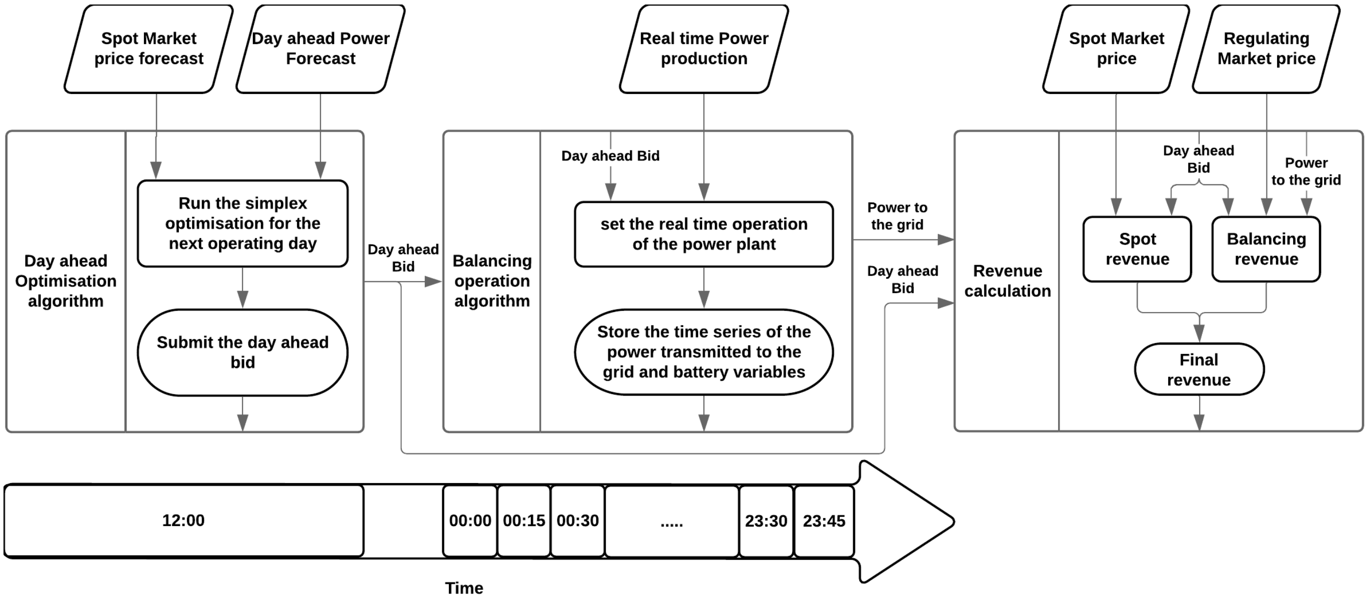


Fig. 1. Full operation algorithm

power bid, P_t^{spot}. Equation (2) ensures that HPP is not producing more than its rated capacity, P_{max}^{HPP}. Equation (3) ensures energy balance, where $\widehat{P}^{res}$ is power generation by renewable generation sources, P^{cha}, P^{dis} are charging and discharging power to the battery respectively. Curtailment is not considered because it negates the objective of maximizing revenue. Equations (4) and (5) constraints that the battery does not charge and discharge at the same time, where P_{max}^{BESS} is power rating of the battery. Equations (6) and (7) set the power flows of the battery to be positive. Equation (8) is setting the limits to the battery SOC. The initial state of charge $\widehat{SOC}_{start}$ in (9) is estimated using the known SOC at the calculation time and simulate operation based on the day ahead forecast and the battery flows decided by the previous day ahead algorithm. The only added knowledge compared to the decisions made on the day before is the current state of charge. Equation (10) is modelling the evolution of the SOC over time due to leakage (efficiency, η_{leak}), charge (efficiency, η_{cha}) and discharge (efficiency, η_{dis}).

It is also possible to add a constraint for setting the SOC at the end of the bidding period. As is, for maximising the revenue, the algorithm will sell all the power stored in the battery before the end of the bidding time, having a null SOC after each bidding time without considerations for the next day of operation. However, it has been observed that the lowest prices of the day (in the considered market) are found in the hour range between 00:00 and 4:00 and therefore it might not be problematic that the battery is totally discharged at the end of one day in order to be able to take advantage of the lowest prices in early morning. However, the equation (11) can optionally be added to set an end goal to SOC, SOC_{goal} at the end of the bidding day.

$$SOC_t = SOC_{goal} \qquad t = t_{24} \tag{11}$$

This equation can lead to an infeasible problem in the case when the wind is blowing full power and the battery is not able to discharge because the grid connection is already congested by the wind power produced. To tackle this issue, (11) has been relaxed and the objective function is modified as shown in (12) and (13).

$$\Pi_d^{spot} = \sum_{t \in T} (\widehat{\lambda}_t^{spot} \cdot P_t^{spot}) - 10^6 \cdot SOC_{mismatch} \tag{12}$$

$$|SOC_t - SOC_{goal}| \leq SOC_{mismatch} \qquad t = t_{24} \tag{13}$$

$SOC_{mismatch}$ measures the mismatch between the SOC wanted at the end of the period and the SOC set at the end of the period. A high cost is associated to having this mismatch in order to force the optimisation algorithm to set it to zero most of the time except when not possible due to meteorological reasons.

B. Balancing Operation Algorithm

The approach developed for balancing market is to use the battery in order to reduce the balancing costs. Therefore, the implemented algorithm is set to compensate the bidding error i.e. error between day ahead scheduled power and real production. Balancing settlement in Nordic market is carried out every 15 mins. The algorithm proposed in Fig. 2 is aiming for the average scheduled power over the settlement window by storing a variable representing the energy imbalance of the given quarter of hour step. This variable is reset to be equal to zero at the beginning of each new settlement window

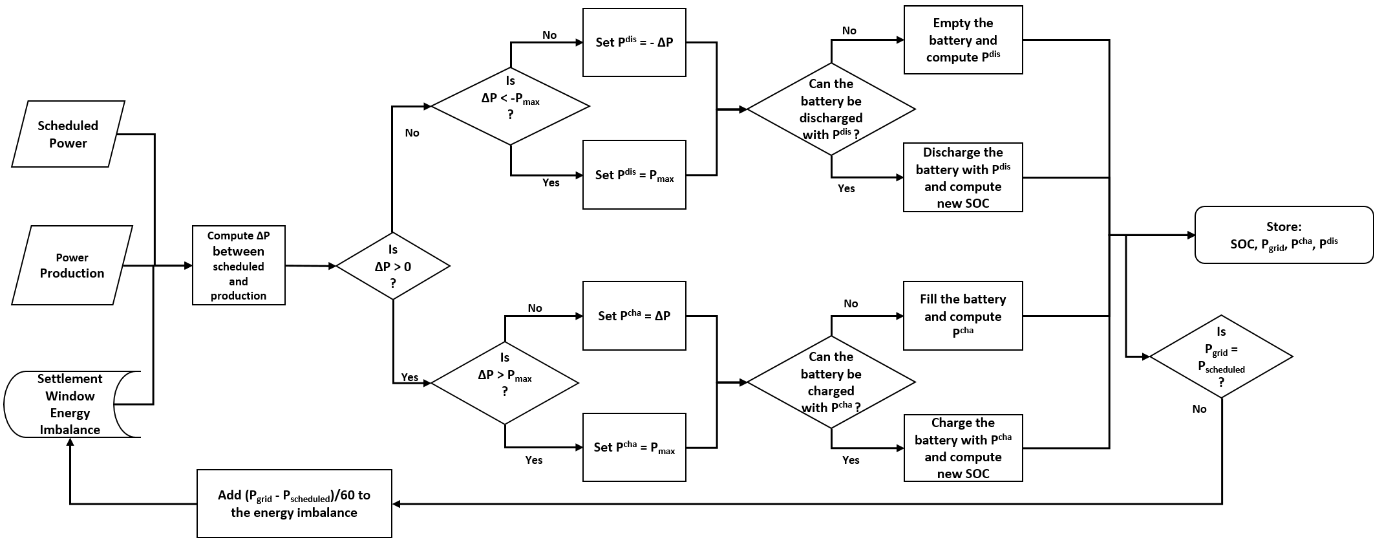


Fig. 2. Balancing operation algorithm aiming for the average scheduled power over the settlement window

and is incremented by the mismatch energy whenever the power transmitted to the grid is different from the scheduled power. Mismatch power, ΔP is computed as the difference between the schedule and the production added to the required power necessary to offset the energy imbalance as detailed in (14). This power difference is aimed to be supplied by either charging or discharging the battery depending on the sign of the power difference and SOC of the battery.

$$(\Delta P)_t = P_t^{res} - P_t^{spot} + \frac{1}{\Delta T}\int_{t_0}^{t}(P_t^{grid} - P_t^{spot})dt \quad (14)$$

- P^{res} Power generation by the renewable energy sources (in this case wind turbines) in MW
- ΔT is the time resolution for which the optimisation is done; considered as 1 minute.
- t_0 and t are respectively the starting time of the settlement window and the current time.

The battery is discharged until the lower SOC limit of the battery and charged until the upper SOC limit of the battery.

C. Revenue Calculation

During actual operation, the grid operator activates up or down regulating power based on the imbalance in the grid, which leads to up and down prices respectively. The day-ahead revenue, $\Pi^{dayahead}$ is calculated by multiplying scheduled power, P^{spot} by spot price, λ^{spot} for the same hour as shown in (15).

$$\Pi_t^{dayahead} = \lambda_t^{spot} \cdot P_t^{spot} \quad (15)$$

Balancing revenue $\Pi^{balancing}$ is equal to the difference between the previous bids and the generated power multiplied by the up price λ^{up} or down price λ^{down} according to the sign of the delta (16). The energy delta between the production and the bid is settled by the system operator on quarter hourly basis [12].

$$\Pi_t^{balancing} = \sum_{q\in[0,3]} \Delta_{t,q}^{+} \cdot \lambda_t^{down} - \Delta_{t,q}^{-} \cdot \lambda_t^{up} \quad (16)$$

where positive power imbalance, Δ^+ and negative power imbalance, Δ^- are defined according to equations (17) and (18).

$$\Delta_{t,q}^{+} = max(0, 4 \cdot \int_{t+\frac{1}{4}\cdot q}^{t+\frac{1}{4}(q+1)} \left(P_t^{grid} - P_t^{scheduled}\right) ds) \quad (17)$$

$$\Delta_{t,q}^{-} = -min(0, 4 \cdot \int_{t+\frac{1}{4}\cdot q}^{t+\frac{1}{4}(q+1)} \left(P_s^{grid} - P_t^{scheduled}\right) ds) \quad (18)$$

In both equations (17) and (18), $P_t^{scheduled}$ is used to refer to the total scheduled power from the previous markets that the producer is expected to generate during an hour. P_s^{grid} is the time series of the measured generation at the point of connection. These deltas are considered to be the average power imbalance over a quarter of hour.

III. Case Study and Results

A. Description of the study cases

Several case studies are performed to analyse the value of using battery storage together with wind power in a HPP. The parameters used to describe the HPP are presented in Table I based on [13] and [7]. The optimisation models presented

TABLE I
HPP PARAMETERS

Name	Value	Unit
P_{max}^{HPP}	51	MW
P_{wind}	51	MW
P_{max}^{BESS}	34	MW
SOC_{max}	245	MWh
SOC_{min}	0	MWh
$SOC_{startOfYear}$	$50\% \cdot SOC_{max}$	MWh
η_{char}	0.95	MW/MW/hour
η_{dis}	0.95	MW/MW/hour
η_{leak}	0	MW/MWh/hour

in the previous section are solved using the simplex solver of IBM Decision Optimisation Studio CPLEX through the docplex python library [14].

B. Study Case - Value of day ahead optimisation

In the first study case, added value of day ahead optimisation is analysed. A perfect forecast scenario, called "Oracle" scenario has been considered as base case to analyse the value of forecast. Forecast for wind power is obtained from CorRES [15], while forecast for spot market are derived through a machine learning based LSTM model (and referred as LSTM henceforth in the results) using historical consumption, production and market prices data for last few years from Nordpool [16]. The consumption, production and wind production prognosis as well as market prices have been chosen as predictors for spot market forecast. The model is trained using data from 2014 and 2015 and then daily forecast is calculated for 2016. However, since any forecast methodology can be used for the studies, details on forecast methods is excluded from the paper. Both for oracle and LSTM, added revenue is compared with respect to the base scenario of operating the WPP without battery storage. Three scenarios are compared in Fig. 3 - i) Operation without battery, ii) Utilizing the battery only for balancing the forecast error, iii) Full utilization of the battery through the optimization model as well as balancing operation is described in section II.

In all of these scenarios, the end of the day SOC is set free and therefore will most likely empty the battery at the end of the day. All these cases have been computed over the full year of 2016 with a starting SOC of 50% of the energy capacity.

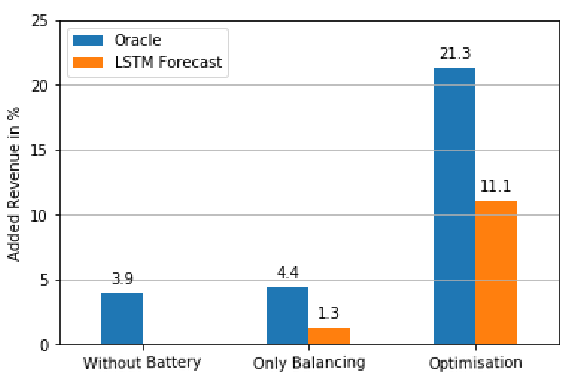


Fig. 3. Comparison of added revenue for different scenarios relative to bidding the forecast without battery

Fig. 3 shows the added revenue over the full year for each of the cases as compared to operate the WPP without battery. Battery used only for balancing doesn't add much revenue compared to allowing for day ahead optimisation. In the "LSTM forecast" case, the added revenue for balancing is approximately 1% while when used in the day ahead market increase the revenue by more than 10%. This figure also demonstrates the importance of improving the accuracy of the power forecast. When operating in the day ahead market the forecast become even more valuable and could help increase the revenue by up to another 10% as demonstrated by "Oracle" case.

TABLE II
REVENUES FOR THE ORACLE SCENARIOS - WITH OPTIMISATION, WITHOUT OPTIMISATION (ONLY BALANCING) AND WITHOUT BATTERY

	Oracle	Oracle_woOpti	Oracle_woBatt
ContractedEnergy [MWh]	164 810	171 681	171 681
surplus [MWh]	1 760	0	6 441
shortage [MWh]	-2 098	-743	-6 441
DownCost	4 913	0	19 945
UpCost	10 083	2 037	21 056
RevenueTOT [M€]	**5,338**	**4,594**	**4,577**
RevenueSPOT [M€]	5,386	4,618	4,618
RevenueBAL [€]	-47 478	-24 304	-41 001
AverageDownCost [€/MWh]	21,2	24,3	26,1
AverageUpCost [€/MWh]	40,4	32,7	32,4

Revenues for the oracle and LSTM scenarios - without battery, with a battery only for balancing and with day ahead optimisation are shown in Tables II and III respectively. The surplus and shortages are calculated as the sum of respectively all the up and down regulation imbalances. Oracle scenarios still have some balancing costs although the production is known in advance. This is due to the Danish market structure where imbalances are settled over quarter of hours while the spot bids are done hourly. During a given hour the quarter hourly average might not be equal to the hourly average. This is translated in the oracle case without battery by having a mismatch cost (UpCost+DownCost) of around 41 k€ (negligible with respect to the total revenue). In the Oracle-only balancing scenario, most of the imbalances are compensated since total revenue is close to the spot revenue. The shortage seen in this case is directly related to the energy loss due to the battery efficiency. Battery reduces the balancing revenue from 41 k€ to 24 k€ (negligible with respect to the total revenue) but most importantly, it reduces the mismatch cost to 2 k€. Finally, in Oracle-day ahead optimisation scenario, mismatch costs increase (still lower than the case without battery) and significant increase in the spot revenue.

TABLE III
REVENUES FOR LSTM FORECAST SCENARIOS - WITH OPTIMISATION, WITHOUT OPTIMISATION (ONLY BALANCING) AND WITHOUT BATTERY

	LSTM	LSTM_woOPti	LSTM_woBatt
ContractedEnergy [MWh]	171 553	171 190	171 190
surplus [MWh]	18 543	13 813	36 654
shortage [MWh]	-25 182	-15 696	-36 162
DownCost	56 222	33 863	108 148
UpCost	109 308	36 709	106 304
RevenueTOT [M€]	**4,891**	**4,462**	**4,404**
RevenueSPOT [M€]	5,405	4,622	4,622
RevenueBAL [€]	-513 688	-160 247	-217 880
AverageDownCost [€/MWh]	21,8	25,6	26,2
AverageUpCost [€/MWh]	36,5	32,7	32,5

It can be observed from Table III that the balancing revenue is increased by 145% in the optimisation case compared to the case without battery (from 218 k€ to 514 k€). This implies loss in revenue, although it is compensated by the increase in revenues from the spot market. However, the mismatch cost associated to these decisions is around 165 k€ (so less than half of the regulating revenue). This implies that if all the power would have been sold in the spot market, the total revenue would have increased only by 165 k€ (negligible with respect to total revenue). Overall, the scenario including spot optimisation with the forecast has a higher revenue than the Oracle scenario without batteries.

The number of equivalent cycles for battery have been calculated based on [17]. It is observed that number of cycles is 30 and 89 for Oracle and LSTM - without optimisation scenario respectively and 285 and 263 for Oracle and LSTM - with optimisation scenario. It is worth noting that even though the scenario that include day ahead optimisation and perfect information has a higher revenue, it also requires higher number of cycles compared to the forecast scenario. Finally, the values found for the number of cycles are in the range of the lifetime of the battery (typically 5000 cycles) and the wind turbines.

C. Sensitivity studies for SOC final value

Since, final value of SOC is an important criterion for optimization model, sensitivity studies are performed in 2 methods for different final values of SOC. In the first method, a fixed goal is set for SOC_{goal}. In the second method, remaining stored energy at the end of the bidding window is economically valued (C). C have been chosen according to spot price distribution over the year and have been set constant over the full year as shown in Fig. 4 .

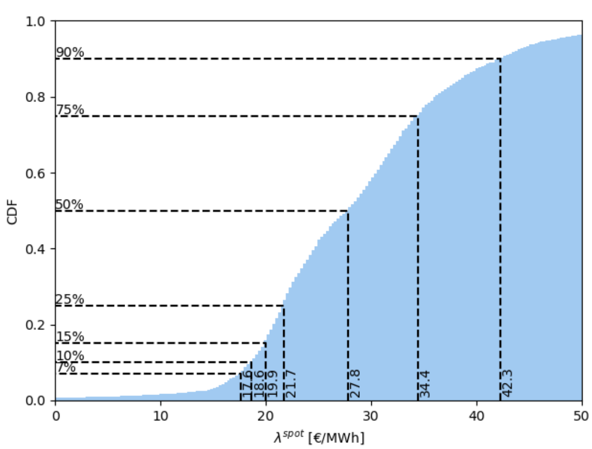
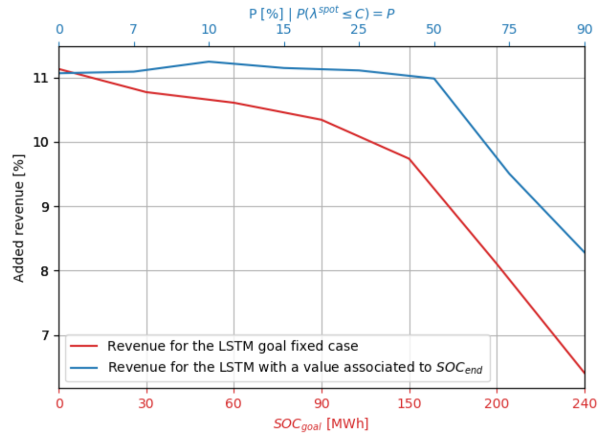
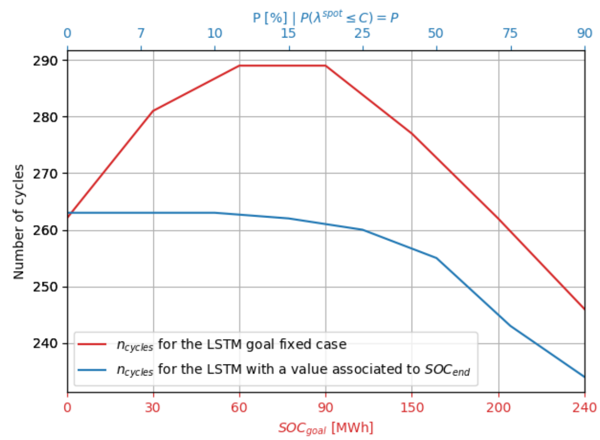


Fig. 4. Cumulative distribution of spot price over the year 2016

Fig. 5a presents the evolution of the additional revenue compared to the case without battery in function of the various SOC_{goal} or in function of the value associated to the final SOC. Valuing approach yields higher revenues than the goal setting approach with a maximum revenue obtained for a cost equal to 18.6 €/MWh for which only 10% of the yearly prices are lower. The highest revenue is equal to 4900 k€ but represents an improvement of only 8 k€ compared to the case where the SOC is set free (see Table III). Cases for which the goal is set free and for which the goal is set to be null lead to equal revenues.



(a) Additional yearly revenues



(b) Number of cycles

Fig. 5. Variation of the additional revenue and the number of cycles for the various SOC_{goal} in red and C in blue

Even though the best scenario does not improve much the revenue, it is interesting to note that the goal setting approach seems much worse regarding the battery lifetime. As shown in 5b, the number of cycles for the valuing energy approach does not use more than 263 cycles over the year while the scenario having a goal of 60 MWh uses 290 cycles over the year, implying higher energy losses and lower lifetime of the battery.

D. Sensitivity studies of power energy ratio of the battery

Scenario of valuing the remaining energy at the end of the day with a value equal to 18.6 €/MWh is used for sensitivity studies of power energy ratio of the battery. It should be noted that economic analysis of the cost of battery is not considered in this study.

Additional revenues for different energy capacity of the battery as shown in Fig. 6 demonstrates that additional revenue is exponentially increasing with high energy capacity for a

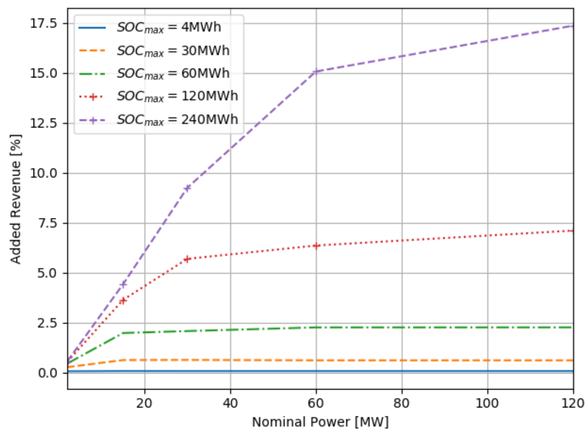


Fig. 6. Revenues in function of the energy capacity of the battery for various power ratings

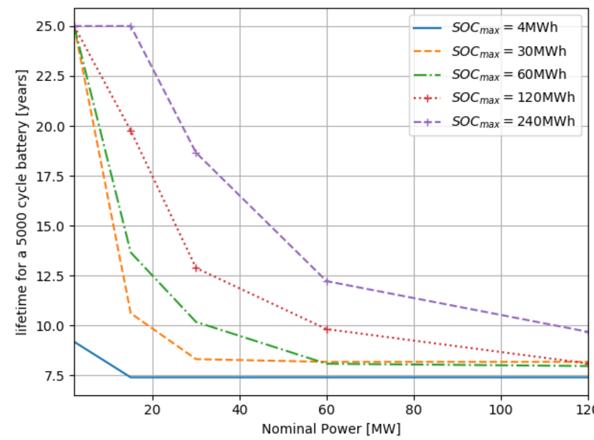


Fig. 7. Life time of the BESS for the various scenarios

considered nominal power rating. However, the value of an additional MWh of capacity is lower in the case when it lacks power capacity (even with high energy rating). This decrease starts to appear for a ratio such that the battery has a capacity of 4 hours its nominal power. Below that threshold, it seems that there is less economic interest in adding a battery. Another interesting highlight of Fig. 6 is that for the case with 30 MW nominal power capacity, the additional revenue with 120 MWh is more than half the additional revenue associated to a capacity of 240 MWh. If the battery price is linear in function of the battery capacity this would mean that a battery of 30MW/120MWh is more profitable per unit invested than a battery of 30MW/240MWh.

The life duration analysis is done assuming that the battery has a minimum cycle life of 5000 cycles and that its calendar life does not exceed 25 years [18]. Fig. 7 displays the lifetime associated to each scenario in a similar way as in Fig. 6. The scenario using a battery of 30MW/120MWh has a much shorter lifetime than the scenario using the 30MW/240MWh one. It can also be seen that in general increasing the battery nominal power is reducing its lifetime quite drastically while increasing the energy capacity has an opposite effect.

Finally, sensitivity studies are performed to compare the value of the battery relative to the case for which no battery is used or for which the battery is used only for balancing as shown in Fig. 8. When using the battery only for balancing the revenue is very low for most energy capacities. Even for the highest energy capacity of 240 MWh, the added revenue only increases by 1% compared to the case without battery. However, the added revenue is higher considering day-ahead optimisation even with smaller battery capacity (4 times for 120 MWh and double for 60 MWh battery).

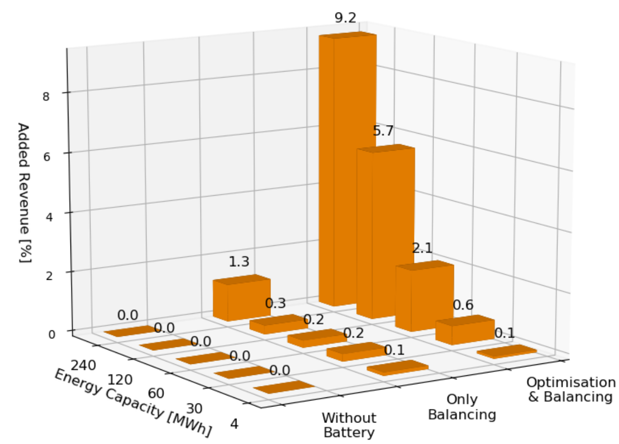


Fig. 8. Added revenue for various energy capacity at a fixed rated power of 30 MW for different optimisation scenarios.

IV. Conclusion

This paper develops an integrated bidding optimisation and balancing methodology to optimally control battery storage in wind-storage HPP. Results in this paper have shown that storage system could be managed in several ways and that scheduling the production based on the market price forecast is the most effective. An integrated bidding strategy for both day ahead markets and balancing markets have been developed. Applying such strategy is eventually increasing the revenue by more than 10% compared to the case without battery. An approach to bridge the gap between bidding windows has been assessed and it has been found that the most efficient technique relative to revenue and life time maximisation was to value the remaining energy rather than constraining the SOC goal to a given value. An analysis has been performed on the sensitivity of the results relatively to the battery power and energy ratings. and it has been shown that the lifetime considerations plays important role when choosing the battery capacity. Since, battery lifetime and cost plays a crucial role in the optimal decision of battery dispatch, it will be natural choice to include the battery cost and lifetime in future research of hybrid power plant's profit maximization.

References

[1] K. Das *et al.*, "Enhanced features of wind based hybrid power plants," in *Proceedings of the 4th International Hybrid Power Systems Workshop*, 2019.

[2] S. Teleke, M. E. Baran, S. Bhattacharya, and A. Q. Huang, "Optimal Control of Battery Energy Storage for Wind Farm Dispatching," *IEEE Transactions on Energy Conversion*, vol. 25, no. 3, pp. 787–794, sep 2010.

[3] D. L. Yao, S. S. Choi, K. J. Tseng, and T. T. Lie, "Determination of short-term power dispatch schedule for a wind farm incorporated with dual-battery energy storage scheme," *IEEE Transactions on Sustainable Energy*, vol. 3, no. 1, pp. 74–84, 2012.

[4] A. Skajaa, K. Edlund, and J. M. Morales, "Intraday Trading of Wind Energy," *IEEE Transactions on Power Systems*, vol. 30, no. 6, pp. 3181–3189, nov 2015.

[5] F. Luo *et al.*, "Coordinated operational planning for wind farm with battery energy storage system," *IEEE Transactions on Sustainable Energy*, vol. 6, no. 1, pp. 253–262, 2015.

[6] Q. Li, S. S. Choi, Y. Yuan, and D. L. Yao, "On the determination of battery energy storage capacity and short-term power dispatch of a wind farm," *IEEE Transactions on Sustainable Energy*, vol. 2, no. 2, pp. 148–158, 2011.

[7] M. Yekini Suberu, M. Wazir Mustafa, and N. Bashir, "Energy storage systems for renewable energy power sector integration and mitigation of intermittency," *Renewable and Sustainable Energy Reviews*, vol. 35, pp. 499–514, 2014.

[8] J. L. Crespo-Vazquez, C. Carrillo, E. Diaz-Dorado, J. A. Martinez-Lorenzo, and M. Noor-E-Alam, "Evaluation of a data driven stochastic approach to optimize the participation of a wind and storage power plant in day-ahead and reserve markets," *Energy*, vol. 156, pp. 278–291, aug 2018.

[9] ——, "A machine learning based stochastic optimization framework for a wind and storage power plant participating in energy pool market," *Applied Energy*, vol. 232, pp. 341–357, dec 2018.

[10] I. L. R. Gomes, H. M. I. Pousinho, R. Melício, and V. M. F. Mendes, "Stochastic optimization for the daily joint operation of wind/pv and energy storage," in *Technological Innovation for Smart Systems*, 2017, pp. 277–286.

[11] P. Pinson, C. Chevallier, and G. N. Kariniotakis, "Trading wind generation from short-term probabilistic forecasts of wind power," *IEEE Transactions on Power Systems*, vol. 22, no. 3, pp. 1148–1156, 2007.

[12] Energinet, "Regulation C2 - The balancing market and balance settlement," https://en.energinet.dk/-/media/1933526FA3974D8D970365F9F851EDB1.pdf, May 2019, accessed on 04 Oct, 2019.

[13] R. Christensen, *Na-S battery*. Danish Energy Agency, 2018, pp. 129–146.

[14] "IBM Decision Optimization CPLEX Modeling for Python," https://github.com/IBMDecisionOptimization/docplex-doc, accessed on 3 October 2019.

[15] M. Koivisto, K. Das, F. Guo, P. Sørensen, E. Nuño, N. Cutululis, and P. Maule, "Using time series simulation tool for assessing the effects of variable renewable energy generation on power and energy systems," *Wiley Interdisciplinary Reviews: Energy and Environment*, p. e329, 2019.

[16] Nordpool, "Historical market data," https://www.nordpoolgroup.com/historical-market-data/, May 2019, accessed on 04 Oct, 2019.

[17] A. Nottrott, J. Kleissl, and B. Washom, "Energy dispatch schedule optimization and cost benefit analysis for grid-connected, photovoltaic-battery storage systems," *Renewable Energy*, vol. 55, pp. 230–240, jul 2013.

[18] International Renewable Energy Agency(IRENA), "Electricity storage and renewables: Costs and markets to 2030," https://www.irena.org/publications/2017/Oct/Electricity-storage-and-renewables-costs-and-markets, pp. 95–99, 2017, accessed on 3 October, 2019.