Optimal Participation of Co-located Wind-battery Plants in Sequential Electricity Markets

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***Abstract*—Since hybrid power plants (HPPs) play an intensive role in the energy supply balance of future energy systems, there is today an increased attention on co-located wind-battery HPPs both in industry and academia. However, the profitability of HPPs in sequential electricity markets to overcome initial investment costs has not been yet well examined, especially with respect to balancing services provision. This article proposes a novel energy management system (EMS) for optimal participation of wind-battery HPPs in two sequential electricity markets, namely in spot market and balancing market. The methodology consists of three optimization models, which allow HPPs to achieve energy arbitrage, to provide balancing services, and to reduce real-time imbalance costs. Furthermore, the profitability of HPPs in future (2030) energy scenario is analyzed based on the new designed and developed EMS taking balancing service into account. The results of the overplanting case show that HPPs operated based on the proposed EMS achieve net present value 3.6 times as high as sole operation in spot market.**

***Index Terms*—wind-battery hybrid power plant, EMS, balancing market, net present value, long-term economic benefits**

NOMENCLATURE

A. Sets

$\mathcal{T}$	Set of hours.
$\mathcal{D}_i$	Set of dispatch intervals.
$\mathcal{S}_i$	Set of settlement intervals.
$\mathcal{K}_s$	Set of dispatch intervals in a settlement interval.

B. Constants

N_D	Number of dispatch intervals in a day.
N_S	Number of settlement intervals in a day.
N_D^O	Number of dispatch intervals in an offering interval.
N_S^O	Number of settlement intervals in an offering interval.
N_D^S	Number of dispatch intervals in a settlement interval.
α_{SEI}	Coefficients of semi-empirical model.
β_{SEI}	Coefficients of semi-empirical model
E^{BESS}	The rated energy capacity of battery energy storage system.
$\hat{\lambda}_t^{sp}$	Spot price forecast at period t (€/MWh).
$\hat{\lambda}_k^{rp}$	Regulation price forecast at period k (€/MWh).
$P^{b,max}$	Maximum output power of battery (MW).
η_{leak}	Hourly battery natural discharging rate (%).
η_{dis}	Hourly battery discharging efficiency (%).
η_{cha}	Hourly battery charging efficiency (%).
η_{leak}^{ha}	Battery natural discharging rate for every 5 minutes (%).
η_{dis}^{ha}	Battery discharging efficiency for every 5 minutes (%).
η_{cha}^{ha}	Battery charging efficiency for every 5 minutes (%).
E^{max}	Maximum energy capacity of battery (MWh).
E^{min}	Minimum energy capacity of battery (MWh).
P^{grid}	Maximum grid capacity (MW).
$\hat{P}_t^w$	Day-ahead wind power forecast at period t (MW).
$\hat{P}_k^w$	Hour-ahead wind power forecast at period k (MW).
$P^{crt,up}$	Offered up regulation power for current OI (MW).
$P^{crt,dw}$	Offered down regulation power for current OI (MW).
$P^{nxt,up}$	Offered up regulation power for next OI (MW).
$P^{nxt,dw}$	Offered down regulation power for next OI (MW).

C. Variables

d^{sem}	Estimated battery degradation by semi-empirical model.
P_t^{sm}	Power schedule offered to spot market at period t (MW).
$P_t^{sm,w}$	Power schedule of wind offered to spot market at period t (MW).
$P_t^{sm,dis}$	Discharging power schedule of battery at period t (MW).
$P_t^{sm,cha}$	Charging power schedule of battery at period t (MW).
$E_t^{sm,b}$	Energy schedule of battery at period t (MWh).
E^{BESS}	The rated energy capacity of battery energy storage system.
$\hat{\Pi}_k^{reg}$	Optimized regulation revenue at period k (€).
Π_k^{reg}	Realized regulation revenue at period k (€).
$\hat{\Pi}_k^{im}$	Optimized imbalance revenue at period k (€).
Π_k^{im}	Realized imbalance revenue at period k (€).
P_k^{up}	Up regulation power offer at period k (MW).
P_k^{dw}	Down regulation power offer at period k (MW).
$\Delta\hat{P}_s^{up}$	Positive imbalance power at period s (MW).
$\Delta\hat{P}_s^{dw}$	Negative imbalance power at period s (MW).
$\Delta\hat{P}_s$	Imbalance power at period s (MW).
P_k^{ha}	Hour-head power schedule at period k (MW).
$P_k^{ha,w}$	Hour-head power schedule of wind at period k (MW).
$P_k^{ha,b}$	Hour-head power schedule of battery at period k (MW).
$P_k^{ha,dis}$	Hour-head discharging power schedule of battery at period k (MW).

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$P_k^{ha,cha}$ Hour-head charging power schedule of battery at period k (MW).

$E_t^{ha,b}$ Hour-ahead energy schedule of battery at period k (MWh).

I. Introduction

THE green transition of energy system is witnessing an increase in share of renewable energy [1]. Nevertheless, the power system imbalances caused by variability and uncertainty of renewable power generations bring huge challenges to power system operators [2]. Such power systems require large power capacity reserves or huge curtailment of renewable power to maintain power system balance. In this respect, energy storage technologies are seen as potential solutions to mitigate such concerns. These storage technologies can either be connected directly in the power systems close to loads or together with renewable power plants (RPPs). If these storage technologies are connected to RPPs (combination typically called hybrid power plants (HPPs)), the storage can be then utilised by the power plant owner to maximize profit from the energy markets through energy arbitrage and provision of ancillary services.

Recently, commercial projects on hybrid renewable energy and battery storage have been developed or are in pipeline in many countries and regions [3]–[5]. For example, the utility-scale HPP - Kennedy Energy Park has been constructed in Queensland, Australia in 2019. In this project, 12 wind turbines amounting 43 MW installed capacity are coupled with 15 MW of solar photovoltaic (PV) and 2 MW/4 MWh of battery energy storage system (BESS) [3]. A larger European utility-scale HPP, Haringvliet Energy Park in Netherlands includes a 22 MW wind farm, a 38 MW solar farm and a 12 MWh energy storage unit [4]. In these renewable HPP projects, the RPPs and energy storage systems are connected to the grid at same point of connection (PoC), sharing power plant equipment like transformers and cables, as well as many infrastructures, e.g. substation, and reducing thus the development and investment costs. In terms of resources utilization, an HPP can increase annual energy production and capacity factor (i.e. grid utilization factor) by using solar combined with wind. An HPP with storage can also increase generation flexibility because by storing excess energy, which would otherwise be curtailed, more stable and higher power output can be inserted into the electrical grid [3], [6], [7]. This is of high relevance to transmission system operators (TSOs), as the aid of storage can, to some extent, locally eliminate variability and uncertainty of renewable power in comparison to individual RPPs, less balancing efforts being thus required for TSOs.

In addition to cost reduction and improved resource utilization, the development of HPPs has also the advantage of emerging market opportunities, which provide more revenue streams for HPPs [8]. One market opportunity is for example the balancing market, where by voluntarily providing balancing service, HPPs might receive payments higher than spot market. Individual RPPs are less likely to provide balancing service due to their power variability and uncertainty.

There have been various investigations in the literature regarding the short-term optimal offering and bidding challenges of wind-battery HPPs in electricity markets. Most of the existing literature about HPPs is mainly concerned with the offer of energy in day-ahead (DA) and/or intra-day (ID) market to maximize revenues [9]–[14]. Furthermore, some of the investigations consider imbalance costs, which is settled in balancing market [15]–[19]. The DA spot market optimization considering imbalance cost is studied in [15], this model being further improved in [16] by incorporating linear decision rule (LDR) for real-time operation. The parameters of LDR are optimized and obtained in DA stage. A coordinated optimization model where the DA market, ID market and imbalance cost are all optimized concurrently in the DA stage, is presented in [18]. In addition, ancillary services provision by HPPs is becoming another promising revenue stream as described in the literature. The optimal trade of power reserve in reserve market is discussed in [20], [21], while the provision of frequency containment normal reserve (FCR-N) in DA FCR-N market is investigated in [22]. The trade of regulation power in hour-ahead (HA) balancing market is considered as a revenue stream in [23].

Apart from the short-term trade challenges, the long-term profitability of wind-battery HPPs is also studied in [19], [24], [25]. For example, a long-term economic analysis of wind-battery HPP in UK market considering DA market revenue and imbalance cost is presented in [19]. The net present values (NPV) of a market based case and power purchase agreement based cases with and without subsidy are examined. Batteries in [24] are used to balance wind power forecast errors, having as result reduced imbalance costs. The studied cases highlight negative NPV due to the higher investment cost of battery. Similar results are also found in [25], namely that by using battery only for energy arbitrage does not repay the high investment cost.

All aforementioned literature mainly focus on short-term optimal operation of wind-battery HPPs in markets by stacking revenue streams, while those studies examining long-term profitability consider limited revenue streams, especially the absence of balancing revenue, which has been detected as potential revenue for HPPs [26]. Besides, their methodologies neglect the grid capacity as a practical constraint for co-located HPPs. Unlike virtual power plants where the WPP and BESS have separate grid connections, it is possible for HPPs to have the WPP overplanted with BESS with limited grid connection capacity owing to the co-location.

To fill this gap, this article proposes a novel EMS methodology and apply it to perform a NPV analysis over 20-year period, which is a common lifetime of wind turbine [27]. The scope of the work is described in Fig. 1. The short-term operation depicts the EMS and its interface with electricity markets, power management system (PMS), forecasts, as well as how the battery degradation model is integrated. Furthermore, revenues in long-term operation is based on short-term operation and the capital expenditures (CAPEX) and operation expenditures (OPEX) of WPP, BESS, and HPP infrastructures, e.g. grid capacity, are taken into account when calculating NPV. The main contributions of this study are:

- This article proposes a novel EMS methodology including spot market optimization (SMOpt), balancing market optimization (BMOpt) and intra-hour re-dispatch optimization (RDOpt). Unlike [17], [23] that only consider hourly resolution in their methodologies, three different time scales, i.e. offering interval (OI), settlement interval (SI), and dispatch interval (DI), are modeled in the proposed EMS to fit practical requirements from TSOs and markets. In addition, the incorporation of a detailed battery degradation model [28] enables the quantification of non-linear battery degradation costs. The value of wind-battery HPPs providing regulation power, i.e. balancing service in Nordic balancing market is firstly investigated through comparing annual profits of different operation strategies.

- To further investigate the profitability of wind-battery HPPs to overcome initial investment costs, NPV analysis of a overplanting HPP is performed by running the proposed EMS. Comparing with [19], [24], [25] that only consider energy arbitrage or/and imbalance cost reduction in the revenue streams, this research work includes balancing revenue in the NPV calculation as the third revenue stream on top of energy arbitrage and imbalance cost reduction. The CAPEX of HPP infrastructures, i.e. cost of grid capacity and balance of system (BOS) is included in the present study in order to depict a more realistic case of the real-world. The reason to choose overplanting case is that overplanting HPP in respect to grid capacity bring benefits to TSO and society, such as delayed requirement for transmission infrastructure reinforcement, more RES integration with same grid capacity [6].
- The existing literature mainly study current or historical energy scenarios. However, the efficacy of the developed methodology in this work is demonstrated through analyzing future (2030) energy scenario of Western Denmark. The purpose is to quantify balancing market potentials for HPP development in 2030.

The article is structured as following. The formulation of the EMS is presented in detail in Section II. Section III discusses the Case study results and describes the implementation of long-term economy analysis. Finally, the conclusions are given in Section IV.

II. Methodology

This section discusses the methodology of the developed EMS. The workflow of the EMS and battery degradation model are demonstrated in short-term operation block in Fig. 1. The EMS is on top of PMS. It works through three optimizations including DA spot market optimization (given in appendix), HA balancing market optimization and intra-hour re-dispatch optimization. All optimization models integrates a detailed battery degradation model [28]. The inputs of the EMS are external forecasts of wind power and market prices, the updated real time (RT) information from PMS, i.e. HPP controller, and information from markets and TSO. The outputs of the EMS are traded energy and power into markets, and energy set-points to PMS.

A. Battery Degradation Model

In this investigation, a semi-empirical model (SEM) [28] is used to estimate the loss of capacity (LoC) of battery. The formulations are given by:

$$d = \begin{cases} 1-\alpha_{sei}e^{-\beta_{sei}l}-(1-\alpha_{sei})e^{-l}, & if d \leq d_1 \\ 1-(1-d')e^{-(l-l^{'})}, & if d > d_1 \end{cases} \quad (1)$$

$$E_{max} = E^{BESS}\cdot(1-d) \quad (2)$$

Eq. (1) provides the models to be used to express the accumulated LoC d for a fresh battery and used battery after the formation of SEI film, respectively. A pre-defined value d_1, e.g. 8% [28] is used to switch between the models. $d^{'}$ and $l^{'}$ are the LoC and linear degradation rate when d exceeds d_1 at the first time. Eq. (2) estimates the remaining energy capacity E_{max}.

The linear degradation rate l in Eq. (1), calculated by Eq. (3) and (4), depends on the depth of discharge (DoD), the elapsed time, the state of charge (SoC), and the cell temperature.

$$l = \sum_i l_i \quad (3)$$

$$l_i = [S_\delta(\delta)+S_{t_c}(t_c)]S_\sigma(\sigma)S_{t_e}(t_e) \quad (4)$$

for every cycle i, the linear degradation rate l_i is calculated according to four stress factor models: $S_\delta(\delta)$, $S_{t_c}(t_c)$, $S_\sigma(\sigma)$ and $S_{t_e}(t_e)$. Their model details can be found in [28].

It should be noticed that the model is a post-processing model. A rainflow counting [29], [30] need to be implemented on historical SoC profile to obtain cycle DoD, cycle average SoC, cycle number, and cycle time duration. Therefore, the model as it is in this form cannot be directly integrated into optimization.

To solve this problem, a throughput based model is used to approximate the semi-empirical model based on the assumption, that the battery degrades linearly in a short period, e.g. one week. The process is described in Fig. 1. Based on this, the accumulated LoC per MWh throughput, i.e. slope a_d, can be calculated in the short period by:

$$a_d = \frac{d^{sem}}{\sum_{t\in T^{past}}|P_t^b|\cdot\Delta t} \quad (5)$$

where d^{sem} is the LoC obtained by (1). $\sum_{t\in T^{past}}|P_t^b|\cdot\Delta t$ represents the energy throughput for a past period. Then the LoC caused by charging/discharging throughput in a future period can be estimated by:

$$d^{est} = a_d\cdot\sum_{t\in T^{future}}|P_t^b|\cdot\Delta t \quad (6)$$

where $\sum_{t\in T^{future}}|P_t^b|\cdot\Delta t$ is energy throughput for a future period.

B. Balancing Market Optimization

The goal of BMOpt is to optimize regulation power offers and update power schedules based on the updated forecast information, e.g. HA wind power forecast. This model operates hourly, starting from the current OI to the end of the day.

1) Objective function: The objective function in BMOpt is to maximize profits in balancing market, namely:

$$\max \sum_{k\in\mathcal{D}_{(t+1)N_D^O}}\hat{\Pi}_k^{reg}+\sum_{s\in\mathcal{S}_{tN_S^O}}\hat{\Pi}_s^{im}-\hat{\Psi}(P_k^{ha,b}) \quad (7)$$

$$\hat{\Pi}_k^{reg} = (\hat{\lambda}_k^{up}\cdot\hat{r}_k^{up}\cdot P_k^{up}-\hat{\lambda}_k^{dw}\cdot\hat{r}_k^{dw}\cdot P_k^{dw})\cdot\Delta k \quad (8)$$

$$\hat{\Pi}_s^{im} = (\hat{\lambda}_s^{dw}\cdot\Delta\hat{P}_s^{up}-\hat{\lambda}_s^{up}\cdot\Delta\hat{P}_s^{dw})\cdot\Delta s \quad (9)$$

$$\hat{\Psi}(P_k^{ha,b}) = \mu\cdot E^{BESS}\cdot a_d\cdot\sum_{k\in\mathcal{D}_{tN_D^O}}(P_k^{ha,dis}+P_k^{ha,cha})\cdot\Delta k \quad (10)$$

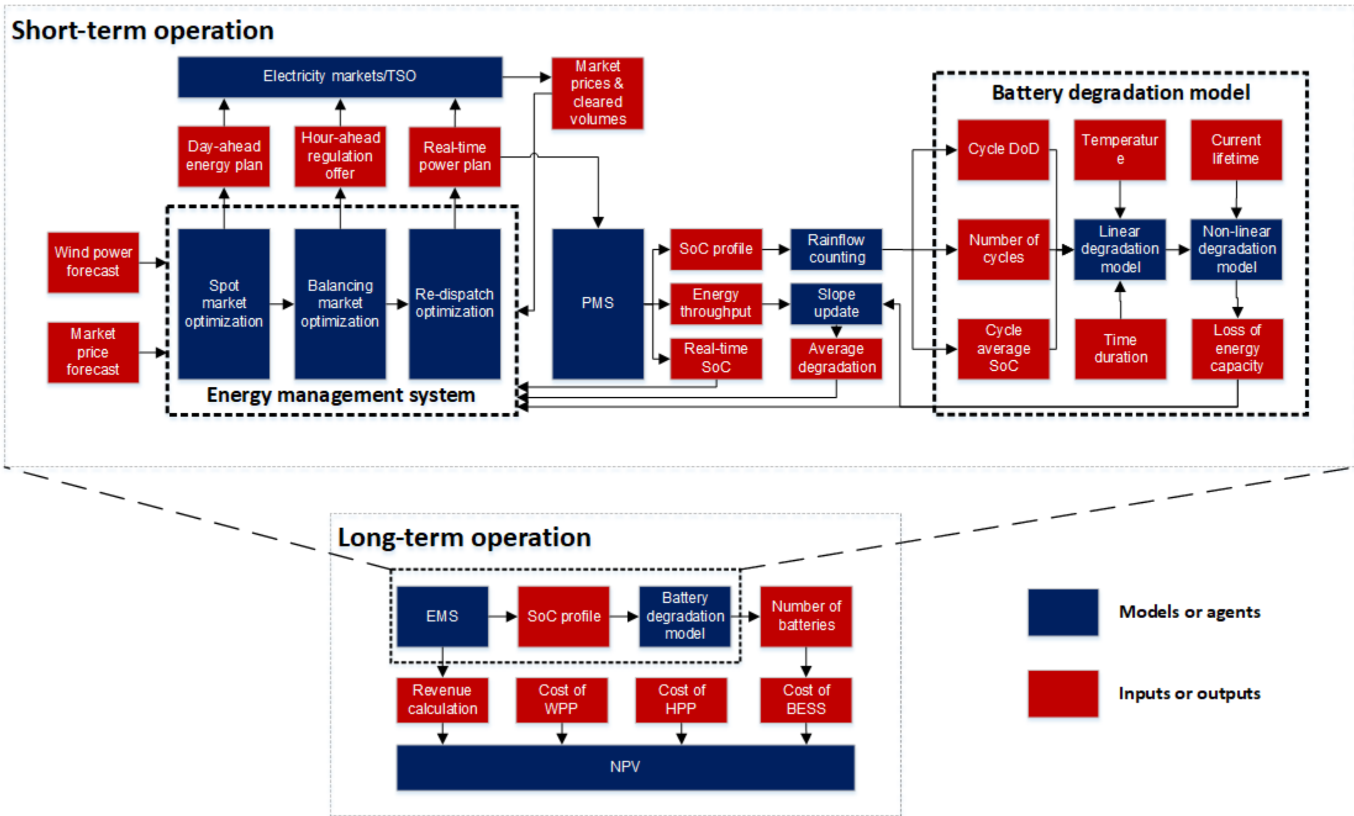

Fig. 1. Diagram of the scope of this research work

Notice that the objective function (7) includes revenues from regulation power and imbalance settlement, as well as penalties of battery degradation. Revenues from regulation power and imbalance settlement are computed in (8) and (9), respectively, where $\hat{\lambda}_k^{up}$ and $\hat{\lambda}_k^{dw}$ are up and down balancing prices, respectively. They are calculated by $\hat{\lambda}_k^{up} = max\{\hat{\lambda}_k^{rp}, \lambda_t^{sp}\}$ and $\hat{\lambda}_k^{dw} = min\{\hat{\lambda}_k^{rp}, \lambda_t^{sp}\}$. The $\hat{\lambda}_k^{rp}$ represents forecasts of regulation price (RP) during period k. It should be noticed that in balancing market optimization, the cleared spot prices (SPs) for all day are known. $\hat{r}_k^{up}$ and $\hat{r}_k^{dw}$ indicate the activation signal of regulation power of coming hour generated by (11) and (12), which can be regarded as forecasts of activation signal. $\hat{\Psi}$ refers to the penalties of battery degradation, given in (10), where μ is the penalty coefficient, which reflects degradation mode. Δk is the DI, which is typically 5 minute resolution. Δs is SI, which is typically hourly or 15 minute resolution. The set $\mathcal{D}_{(t+1)N_D^O}$ is defined as $\mathcal{D}_{(t+1)N_D^O} := \{(t+1)N_D^O, (t+1)N_D^O+1, ..., N_D-1\}$. There is $\mathcal{D}_0 \supset \mathcal{D}_1 \supset \cdots \supset \mathcal{D}_{N_D-1}$. Therefore, the optimization horizon decreases as time increases.

$$\hat{r}_k^{up} = \begin{cases} 1, & \text{if } \hat{\lambda}_k^{rp} > \lambda_k^{sp} \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

$$\hat{r}_k^{dw} = \begin{cases} 1, & \text{if } \lambda_k^{rp} < \lambda_k^{sp} \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

2) Technical and operation constraints: In BMOpt a sub-hourly resolution is applied because TSO requires higher resolution power schedule to balance power system, namely for $k \in \mathcal{D}_{tN_D^B}$:

$$P_k^{ha} = P_k^{ha,w} + P_k^{ha,b} \tag{13}$$
$$P_k^{ha,b} = P_k^{ha,dis} - P_k^{ha,cha} \tag{14}$$
$$0 \leq P_k^{ha,cha} \leq P^{b,max} \cdot (1 - z_k) \tag{15}$$
$$0 \leq P_k^{ha,dis} \leq P^{b,max} \cdot z_k \tag{16}$$
$$E_{k+1}^{ha,b} = E_k^{ha,b}(1 - \eta_{leak}^{ha}) - \frac{P_k^{ha,dis}}{\eta_{dis}^{ha}} \cdot \Delta k + P_k^{ha,cha}\eta_{cha}^{ha} \cdot \Delta k \tag{17}$$
$$E^{min} \leq E_k^{ha,b} \leq E^{max} \tag{18}$$
$$0 \leq P_k^{ha} \leq P^{grid} \tag{19}$$
$$0 \leq P_k^{ha,w} \leq \hat{P}_k^{w} \tag{20}$$

Equation (13) calculates power output of HPP based on wind and battery generation, where P_k^b is calculated in (14). Constraints (15) and (16) limit the battery that cannot charge or discharge at the same time, where $z_t = 1$ means the battery works on discharging status, otherwise $z_t = 0$ means the battery works on charging status. (17) models the evolution of battery energy over time. (18) set the limits of energy. (19) constraints that the power output of HPP cannot exceed grid limitation. (20) restricts wind power output less than the forecasting value.

3) Imbalance settlement constraints: The revenue from imbalance settlement should also be considered when optimizing regulation power offers and power schedules. This refers to whether HPPs should deliberately create imbalance in order to capture revnenue opportunities from providing regulation power. For $s \in \mathcal{S}_{tN_S^O}$, the imbalance settlement constraints are expressed in (21)-(23).

Where $\Delta\hat{P}_s$, $\Delta\hat{P}_s^{up}$ and $\Delta\hat{P}_s^{dw}$ are imbalance power, positive imbalance power and negative imbalance power in a SI. (21) calculates imbalance power that is the difference among HA power schedule and DA promised power as well as regulation power. The set $\mathcal{S}_{tN_S^O}$ is defined as $\mathcal{S}_{tN_S^O} := \{tN_S^O, tN_S^O + 1, \cdots, N_S - 1\}$. There is $\mathcal{S}_0 \supset \mathcal{S}_1 \supset \cdots \supset \mathcal{S}_{N_S-1}$. The set $\mathcal{K}_s$ is defined as $\mathcal{K}_s := \{sN_D^S, sN_D^S+1, \cdots, (s+1)N_D^S - 1\}$.

r_k^{up} and r_k^{dw} are the activation signal of regulation power of current hour coming from TSO. 1 means activation and 0 means no activation.

C. Re-dispatch Optimization

The RDOpt operates between two BMOpts when part of imbalances has been realized. It repeats every 5 minutes, which is a nearly real-time optimization starting from the i_{th} DI to the end of the day. The goal of this model is to update power schedule continuously with real-time information to maximize profits in imbalance settlement and also consider the potential profit opportunities for providing regulation power in the future OIs.

1) Objective function:

$$\max \sum_{k \in \mathcal{D}_{(t+2)N_D^B}} \hat{\Pi}_k^{reg} + \sum_{s \in \mathcal{S}_{\lfloor i/N_D^S \rfloor}} \hat{\Pi}_s^{im} - \hat{\Psi}(P_k^{ha,b}) \quad (24)$$

The objective function of RDOpt is similar with BMOpt, but the difference is that the index of regulation revenues is $\mathcal{D}_{(t+2)N_D^B}$, meaning that the start interval for regulation power offers is after 2 OIs, because regulation power offers for current OI and next OI are already determined at the time of optimization. $\lfloor \cdot \rfloor$ means rounding down.

2) Technical and operation constraints: For $k \in \mathcal{D}_i$, The general constraints are same as BMOpt, i.e. (13)-(20).

3) Imbalance settlement constraints: In the re-dispatch stage, the calculation of imbalance power is classified into four situations: the current SI, the remaining SIs in the current OI, the SIs in the next OI, and the SIs for the rest of the day. For $s \in \mathcal{S}_{\lfloor i/N_D^S \rfloor}$, the constraints are shown in (22), (23) and (25)-(28):

D. Post-calculation of Revenue and Cost

The profits calculation happens after the operation day when all information is realized. Accordingly, the profits can be calculated. The spot market revenue Π^{sm} is calculated by multiplying energy schedule with cleared spot prices:

$$\Pi^{sm} = \sum_{t \in \mathcal{T}} \lambda_t^{sp} \cdot P_t^{sm} \cdot \Delta t \quad (29)$$

Regulation revenue is equal to activated regulation powers multiplied by RPs (30).

$$\Pi^{reg} = \sum_{k \in \mathcal{D}_t} \lambda_k^{rp} \cdot P_k^{reg} \cdot \Delta k \quad (30)$$

where P_k^{reg} is activated regulation power calculated by (31)

$$P_k^{reg} = r_k^{up} \cdot P_k^{up} - r_k^{dw} \cdot P_k^{dw} \quad (31)$$

Imbalance revenue is equal to differences among the real-time measurements and spot market power schedule as well as activated regulation power multiplied by the up price or down price according to the sign of the delta (32).

Fig. 2. An overview of HPP EMS and HPP PMS [31]

$$\Pi^{im} = \sum_{s \in \mathcal{S}_t} (\lambda_s^{dw} \cdot \Delta P_s^{up} - \lambda_s^{up} \Delta P_s^{dw}) \cdot \Delta s \quad (32)$$

where ΔP_s^{dw} and ΔP_s^{up} are realized imbalance power given in (33) and (34).

$$\Delta P_s^{up} = \begin{cases} \Delta P_s, & \text{if } \Delta P_s \geq 0 \\ 0, & \text{otherwise} \end{cases} \quad (33)$$

$$\Delta P_s^{dw} = \begin{cases} -\Delta P_s, & \text{if } \Delta P_s \leq 0 \\ 0, & \text{otherwise} \end{cases} \quad (34)$$

$$\Delta P_s = \sum_{k \in \mathcal{K}_s} (P_k^{rt} - P_k^{reg} - P_k^{sm}) \quad (35)$$

where P_k^{rt} is the real-time measured generation provided by PMS.

Apart from revenues, battery degradation cost is also calculated in (36) to reflect where the battery lifetime is.

$$\Psi = \frac{N_c}{N_c^{total}} \cdot C^{Cap} \quad (36)$$

where N_c^{total} represents the total number of 100%-DOD cycles that makes battery reach to 80% state of health (SoH). C^{Cap} is the capital cost of battery. N_c is the equivalent 100%-DoD cycle number, which can be identified by Eq. (1), (3), and (4) assuming the observed LoC is loaded by repeated cycles with 100% DoD, and 50% average SoC.

E. Real-time measurements

In the real-world, the communication between EMS and PMS is required to exchange information. The interface of EMS with PMS is shown in Fig. 2 [31], where the EMS provides energy set-points to PMS and obtains real-time measurement values, e.g. P_k^{rt} from PMS. However, it is impossible to connect the developed EMS to a real PMS to implement long-term case analysis. To solve this problem, a real-time algorithm to emulate active power control logic [32] is proposed as depicted in Fig. 3.

In each DI, the behavior of controller depends on the difference between available wind power and power reference, battery charging/discharging abilities, and whether the PoC is congested. The final outputs of the algorithm are 3 states with the priority that follow reference > create imbalance > power curtailment.

III. Case studies

A set of case studies is carried out to assess the performance of the proposed EMS methodology for HPPs in sequential electricity markets and to understand the profitability of HPPs in sequential electricity markets towards year 2030. As an HPP located in Western Denmark is considered, the market rules of DK1 are applied, where, the DI, SI, OI are 5 minutes, 15

$$\Delta \hat{P}_s = \begin{cases} \frac{1}{\Delta_s} \cdot \sum_{k\in\mathcal{K}_s} (P_k^{ha} - (r_k^{up} P^{crt,up} - r_k^{dw} P^{crt,dw}) - P_k^{sm}) \cdot \Delta_k, & \text{if } s < tN_S^O \\ \frac{1}{\Delta_s} \cdot \sum_{k\in\mathcal{K}_s} (P_k^{ha} - (\hat{r}_k^{up} P_k^{up} - \hat{r}_k^{dw} P_k^{dw}) - P_k^{sm}) \cdot \Delta_k, & \text{o.w.} \end{cases} \tag{21}$$

$$\Delta \hat{P}_s = \Delta \hat{P}_s^{up} - \Delta \hat{P}_s^{dw} \tag{22}$$

$$\Delta \hat{P}_s^{up}, \Delta \hat{P}_s^{dw} \geq 0 \tag{23}$$

$$\Delta \hat{P}_s = \begin{cases} P_s^{im} + \frac{1}{\Delta_s} \cdot \sum_{k\in\mathcal{K}_s} (P_k^{ha} - (r_k^{up} P^{crt,up} - r_k^{dw} P^{crt,dw}) - P_k^{sm}) \cdot \Delta_k, & \text{if } \ s = \lfloor i/N_D^S \rfloor \quad (25) \\ \frac{1}{\Delta_s} \cdot \sum_{k\in\mathcal{K}_s} (P_k^{ha} - (r_k^{up} P^{crt,up} - r_k^{dw} P^{crt,dw}) - P_k^{sm}) \cdot \Delta_k, & \text{if } \ \lfloor i/N_D^S \rfloor < s < tN_S^O \quad (26) \\ \frac{1}{\Delta_s} \cdot \sum_{k\in\mathcal{K}_s} (P_k^{ha} - (\hat{r}_k^{up} P^{nxt,up} - \hat{r}_k^{dw} P^{nxt,dw}) - P_k^{sm}) \cdot \Delta_k, & \text{if } \ tN_S^O \leq s < (t+1)N_S^O \quad (27) \\ \frac{1}{\Delta_s} \cdot \sum_{k\in\mathcal{K}_s} (P_k^{ha} - (\hat{r}_k^{up} P_k^{up} - \hat{r}_k^{dw} P_k^{dw}) - P_k^{sm}) \cdot \Delta_k, & \text{o.w.} \quad (28) \end{cases}$$

minutes, and 1 hour, respectively. As shown in Table I, four operation strategies are considered in the analysis. It should be noted that since there is no trade of regulation power when use SMOpt and RDOpt, the variables and objective function term regarding regulation power in RDOpt are not considered. The parameters for the HPP, based on [31] and Danish Energy Agency catalogue [33], are depicted in Table II.

All three optimisation models, proposed and described in the previous section, are solved using the solver of IBM Decision Optimisation Studio CPLEX through the docplex python library [34] operating on DTU's high performance computing cluster *Sophia* [35].

TABLE I
OPERATION STRATEGY DEFINITION

Operation strategy	Spot market	Balancing market	
	SMOpt	BMOpt	RDOpt
SM	✓		
SM+RD	✓		✓
SM+BM	✓	✓	
SM+BM+RD	✓	✓	✓

TABLE II
PARAMETERS OF THE HPP

Item	Parameters	Values
WPP	$P^{w,max}$	120 MW
BESS	$P^{b,max}$	20 MW
	E^{BESS}	60 MWh
	E^{min}	12 MWh
	η_{cha}	97%
	η_{dis}	98%
	η_{leak}	0%
	μ	0.142 M€/MWh
	C^{Cap}	11.72 M€
Grid	P^{grid}	100 MW

A. Wind and market data

Wind power time series are simulated with the CorRES simulation tool [36]–[38]. This tool is based on re-analysing meteorological data from the weather research and forecast model with the stochastic model to add fluctuations. CorRES is capable of simulating wind power time series in minute resolution. The longitude, latitude, and hub height of HPP, power curves of wind turbines and simulation period are required as inputs for CoRES to simulate wind power time series. The weather year used for the time series corresponds to 2012. The assumption behind is that the climate in 2030 does not change compared to 2012. DA and HA forecasts of wind power time series are also obtained from CorRES with the same setup. 5-minute-ahead forecasts are generated based on the realized wind power of previous 5 minutes as forecast of next 5 minutes.

The SP and RP in 2030 electricity markets are modeled by balancing tool chain (BTC) [39], which aggregates Balmorel open source energy system model [40] for DA market operation, the balancing model, and the area frequency control model. The goal of BTC is to simulate the operation of energy system with variable renewable energy generation. SP forecast is derived through Long-short term memory network [41]. RP forecast is taken as the last day's realized RP as forecast of current day.

Fig. 4 shows the DA, HA, 5-minute-ahead forecasts and measurements of wind power as well as the actual and forecast spot and regulation price.

B. Annual profit of HPP

It is noticed that in some Nordic countries, there are contractual and legal requirements with regards to participants following their power schedules [42]. For DK1, deviations between participants metering power and most recent power schedules are penalized by a special power imbalance settlement. The settlement is based on original energy notification, most recent updated power schedule converting to 15 minutes resolution time series, and real-time metering power converting to 15 minutes resolution time series. In each 15 minutes, the deviations bigger than 10 MW are punished. The details of calculation can be found in [43]. This part of penalty is also considered to analyze the profitability. Accordingly, the annual statistics of revenues and costs for different operation strategies are shown in Table IV and Fig. 5. Besides, as shown in Fig. 6, one week is picked up randomly to compare the real-time measured power and power schedules for all operation strategies and to analyse whether power schedules are well tracked. Table III demonstrates root mean square error (RMSE) between real-time measured power and power schedules. It is clear in Fig. 6 that with re-dispatch optimization in (b) and (d), HPP can follow its power schedule at more time comparing with (a) and (c). According to Table III, the RMSEs are reduced from 25.5 to 0.7 and from 4.4 to 1.1, respectively. Therefore, the energy set-points obtained by intra-hour re-dispatch are easily to be tracked by PMS. The reason is that 5-min ahead forecast of wind power is more accurate and hence stressing battery less, when following such power setpoints.

TABLE III
RMSE OF P_k^{ref} AND P_k^{rt} IN DIFFERENT OPERATION STRATEGIES

	SM	SM+RD	SM+BM	SM+BM+RD
RMSE	25.5	0.7	4.4	1.1

As observed in Fig. 5 and Table IV, it is clear that the total profit of HPP in the operation strategy SM+BM+RD is biggest (13.7 M€), being followed by the operation strategy SM+BM (13.6 M€) and SM+RD (12.2 M€), respectively, the lowest profit being achieved in the operation strategy SM (10.3 M€). Furthermore, it is also seen that the intra-hour re-dispatch can unilaterally improve the profits of HPP by reducing imbalance costs from 3.9 M€ to 1.8 M€. while providing balancing service can individually improve the profits of HPP by capturing the regulation revenue stream leading to almost none penalties in BM. The comparison illustrates that the profit potential of providing balancing service is higher than real-time imbalance cost reduction. Besides, it can also be noticed that battery degradation cost approximately doubles with operation strategy SM+BM comparing with operation strategy SM. The reason is the fact that battery stresses more when providing balancing service. However, the aid of intra-hour re-dispatch helps the battery degradation cost decrease by comparing operation strategy SM+BM+RD and SM+BM, which illustrates that energy set-points derived from re-dispatch optimization stress battery less.

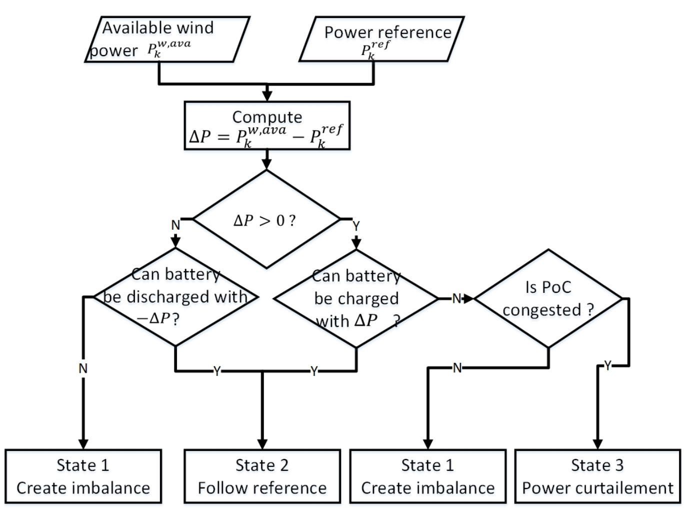

Fig. 3. Real-time simulation algorithm

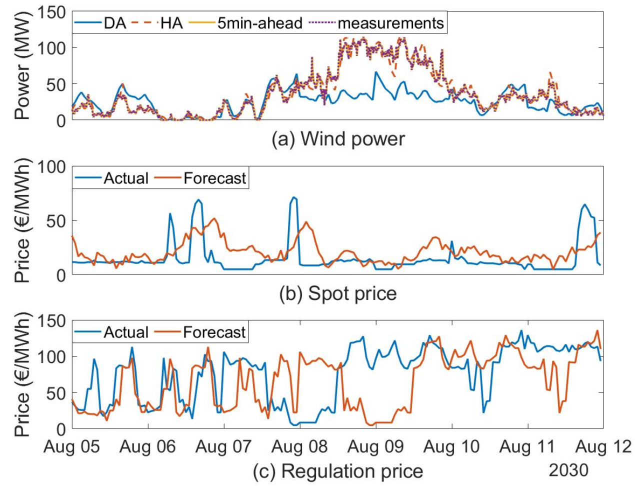

Fig. 4. Demonstration of wind and market data in one week: (a) DA, HA, 5min-ahead forecast and measurement of wind power time series; (b) Forecasted and actual SP time series; (c) Forecasted and actual RP time series

C. Net present value analysis

This subsection analyses the long-term economic performance of the co-located wind-battery HPP by examining NPV over 20 years. The equation to calculate NPV is as follows:

$$NPV = R_{HPP} - C_{WPP} - C_{BESS} - O_{WPP} - O_{BESS} - C_{HPP} \tag{37}$$

where $R_{HPP}, C_{WPP}, C_{BESS}, O_{WPP}, O_{BESS}, C_{HPP}$ represent HPP revenues, the CAPEX of WPP and BESS, the OPEX of WPP and BESS, as well as the cost of grid connection and BOS, respectively. The calculations of each item in (37) are described as follows.

1) HPP revenue: The computation of revenue is not the discount factor based model as reported in [19], [24]. Instead, we run the proposed EMS for several years until the remaining energy capacity of first battery is reaching to 80% of the rated energy capacity, when the battery needs to be replaced [28]. An assumption behind is that market price and wind power times series are identical in every year. However, the incorporation of detailed battery degradation model avoids the general assumption that number of cycles used in every year are constant [19]. Then the HPP revenue can be estimated based on the run of the first battery using (38).

$$R_{HPP} = R^{first} \times (N_b - 1) + R^{last} \tag{38}$$

$$N_b = \lceil \frac{20 \times 365}{D^{first}} \rceil \tag{39}$$

$$R^{last} = \sum_{d=1}^{D^{last}} R_d^{first} \tag{40}$$

where R^{first} and R^{last} are the revenues from the first and last batteries, respectively. N_b is number of batteries used in 20 years. D^{first} and D^{last} are the numbers of operation days of first and last batteries, respectively.

2) CAPEX of BESS: The calculation of CAPEX of BESS is based on [33], where the cost of energy component (62000 €/MWh), power conversion system (PCS) (160000 €/MW), and other project costs (80000 €/MWh) are included.

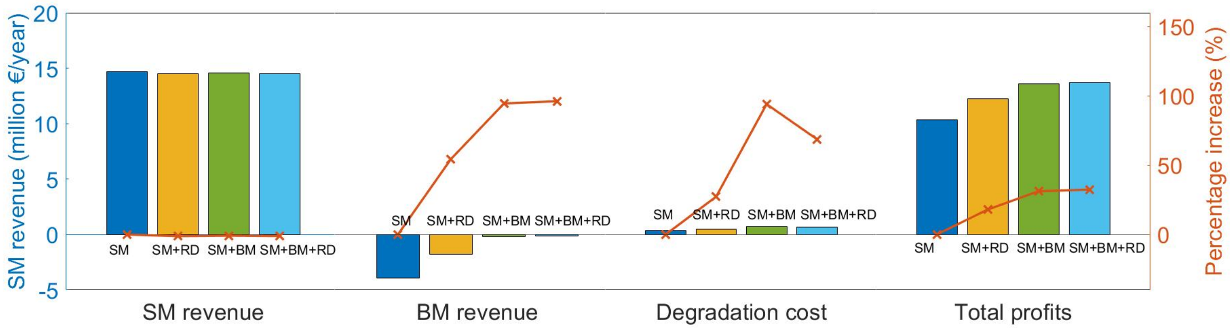

Fig. 5. Comparison of SM revenue, BM revenue, degradation cost and total profits of all operation strategies

TABLE IV
ANNUAL REVENUES AND COSTS OF HPP WITH DIFFERENT OPERATION STRATEGIES (MILLION €)

Operation strategy	SM revenues	BM revenues			Total revenues	Degradation costs	Total profits
		regulation revenues	imbalance revenues	Total			
SM	14.7	0	-3.9	-3.9	10.7	0.4	10.3
SM+RD	14.5	0	-1.8	-1.8	12.7	0.5	12.2
SM+BM	14.6	3.9	-4.1	-0.2	14.3	0.7	13.6
SM+BM+RD	14.5	4.0	-4.1	-0.1	14.3	0.6	13.7

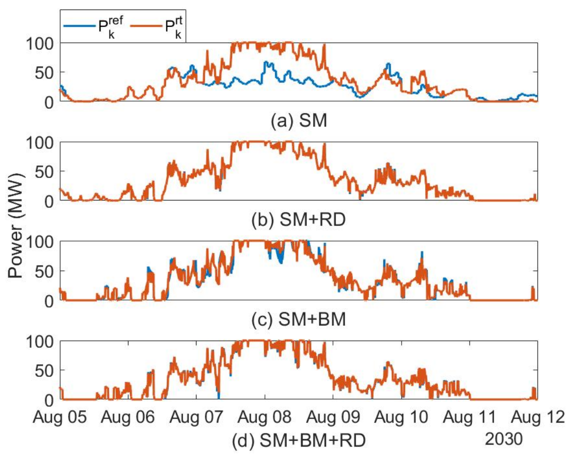

Fig. 6. Real-time power measurements and power schedules with different operation strategies: (a) SM; (b) SM+RD; (c) SM+BM; (d) SM+BM+RD

3) OPEX of BESS: The OPEX consists of fixed and variable operation and maintenance (O&M) cost [33], which are 540 €/MW/year and 1.8 €/MWh, respectively.

4) CAPEX and OPEX of WPP: The CAPEX of WPP considered in this paper are wind turbine cost, civil work cost, which are 851000 €/MW and 117000 €/MW, respectively. The fixed O&M cost of WPP is 12800 €/MW/year.

5) CAPEX of grid connection and BOS cost: Apart from the cost of individual assets, costs of other HPP infrastructures are not negligible. This is categorized as cost of grid connection and BOS, which are 37100 €/MW and 120000 €/MW, respectively.

Based on the above process, the profitability of the overplanting HPP (100 MW grid capacity) for different operation strategies are examined by computing the NPV. Table V depicts all the results of NPV analysis, where E^{total} is 20 years' total dispatched energy of battery, which is related to variable O&M cost and can embody the stress of the BESS. L^{first} is the lifetime of the first battery in years. According to Fig. 8, it is clear that all examined cases yield positive NPV, suggesting a profitable investment for overplanting HPP in 2030. More specifically, the case with SM+BM+RD achieves the highest NPV, which is 1.02 times, 1.55 times, and 3.6 times to SM+BM, SM+RD, and SM operation strategies, respectively, which highlights the profitability of balancing market. Additionally, the case with SM uses 2 batteries during the 20 years while cases with other operation strategies use 3 batteries. This is reasonable that batteries degrades faster when being used for more revenue streams. However, by comparing with SM+BM+RD and SM+BM, intra-hour re-dispatch extends the first battery lifetime for 0.1 years as shown in Table V. It can be also observed from Table V, that the energy throughput of SM+BM+RD is lower than SM+BM, meaning that the operation strategy SM+BM+RD stresses the BESS less. This can be explained from the fact that by utilizing more accurate 5-min ahead forecast, the intra-hour re-dispatch optimization is able to generate more easy-followed energy plan.

Fig. 7 demonstrates the yearly cycles of the first batteries with different operation strategies. It is obvious that cycles of all operation strategies are not constant in every year, instead, it shows an increase trend. The reason is that battery degradation is faster in the early stage and becomes slower gradually, therefore, the proposed EMS uses battery less in the early stage and increases the use afterwards.

IV. CONCLUSION

This article has proposed an EMS for wind-battery HPP in electricity markets, which allows HPPs to obtain revenues from energy arbitrage, provision of balancing service, and reduction of real-time imbalances. The annual simulation of the HPP in sequential electricity markets towards 2030 has been carried out to analyse the performance of EMS. In addition, by considering different revenue streams, the long-term profitability of the overplanting HPP against investment

TABLE V
RESULTS OF NPV ANALYSIS WITH DIFFERENT OPERATION STRATEGIES AND GRID CAPACITIES

Operation strategy	Grid capacity (MW)	R^{total}(M€)	$E^{total}(GWh)$	$L^{first}(years)$	N_b	NPV (M€)
SM	100	214	485	10.7	2	26.1
SM+RD	100	260	822	8.0	3	60.6
SM+BM	100	293	1183	7.0	3	92.2
SM+BM+RD	100	294	1021	7.1	3	94.0

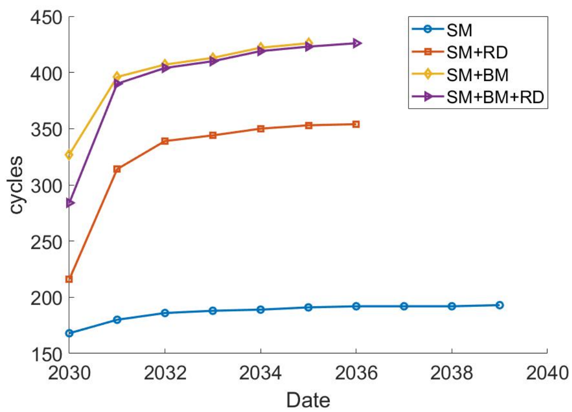

Fig. 7. Annual cycles of the first battery with different operation strategies (the cycles of last year are not plotted due to incomplete year)

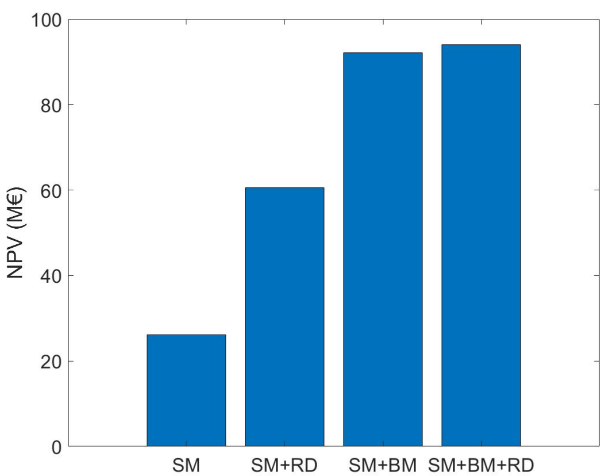

Fig. 8. NPV of the HPP with different operation strategies

has been examined through a set of case studies carried out in Denmark by net present value analysis. The main outcomes of this research are:

- Add intra-hour re-dispatch optimization to spot market optimization or spot market optimization and balancing market optimization enables the power schedules more trackable for power management system. In the studied cases, the root mean square errors reduce from 25.5 to 0.7 or from 4.4 to 1.1, respectively.
- Providing balancing service can improve the profits of HPP by capturing the regulation revenue stream leading to almost none penalties in balancing market.
- It is profitable for operating wind-battery hybrid power plants in 2030 with the developed energy management system. By considering balancing service as another revenue stream on top of energy arbitrage and imbalance cost management, the net present value of the overplanting hybrid power plant has increased around 2.6 times and 55% comparing with only considering energy arbitrage and considering both energy arbitrage and imbalance cost reduction, respectively.

APPENDIX

A. Spot Market Optimization

The goal of spot market optimization is to decide how much energy should be committed into the spot market based on wind power forecasts and spot market price forecasts. This model operates once a day, before the closure of spot market.

1) Objective function: The objective function in the spot market optimization is to maximize profits, i.e. revenues minus degradation cost, in spot market, namely:

$$\max \sum_{t\in\mathcal{T}} \hat{\lambda}_t^{sp} \cdot P_t^{sm} \cdot \Delta t - \hat{\Psi}(P_t^{dis}, P_t^{cha}) \tag{41}$$

where the first item is the revenues by committing energy in spot market. Δt is typically one hour.

2) Technical and operation constraints:

$$P_t^{sm} = P_t^{sm,w} + P_t^{sm,b} \tag{42}$$

$$P_t^{sm,b} = P_t^{sm,dis} - P_t^{sm,cha} \tag{43}$$

$$0 \le P_t^{sm,cha} \le P_t^{b,max} \cdot (1 - z_t) \tag{44}$$

$$0 \le P_t^{sm,dis} \le P_t^{b,max} \cdot z_t \tag{45}$$

$$\begin{aligned} E_{t+1}^{sm,b} = E_t^{sm,b} \cdot (1-\eta_{leak}) - \frac{P_t^{sm,dis}}{\eta_{dis}} \cdot \Delta t \\ + P_t^{sm,cha} \cdot \eta_{cha} \cdot \Delta t \end{aligned} \tag{46}$$

$$E^{min} \le E_t^{sm,b} \le E^{max} \tag{47}$$

$$0 \le P_t^{sm} \le P^{grid} \tag{48}$$

$$0 \le P_t^{sm,w} \le \hat{P}_t^w \tag{49}$$

The constraints in spot market optimization are defined in the similar way as for balancing market optimization, with just the small difference that in spot market optimization hourly resolution is applied according to the requirement from TSO.

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