Profit-optimal data-driven operation of a hybrid power plant participating in energy markets

A Anand[1], J Petzschmann[2], K Strecker[2], R Braunbehrens[1], A Kaifel[2], and C L Bottasso[1]

[1] Wind Energy Institute, Technische Universität München, Garching bei München, Germany
[2] Zentrum für Sonnenenergie- und Wasserstoff-Forschung Baden-Württemberg, Stuttgart, Germany

E-mail: `abhinav.anand@tum.de`

Abstract. An energy management system (EMS) is formulated for a hybrid power plant (HPP), consisting of a wind power plant and battery storage plant, participating in bidding stages in the German energy market. The EMS utilizes supervisory control and data acquisition (SCADA) measurements from the site to improve power forecast from the wind power plant. First, the measurement data is used together with numerical weather prediction data to accurately forecast local wind conditions. Second, the measurement data is used to adapt a baseline engineering wake model that gives the total wind power generation for a given input wind condition. The EMS also uses an online cyclic damage minimization approach to accurately balance the battery damage cost against the revenue obtained by market bidding. An HPP controller is formulated to ensure proper tracking of optimal set-points. When compared with the industry standard, the proposed formulation shows an accurate estimation and balancing of revenue and costs and a significant reduction in the power deviation penalty, which leads to significantly higher overall profit.

1. Introduction

The variability of wind power creates fluctuations in the electricity market prices. As a consequence, the electricity price is typically negatively correlated with wind speed [1]. Wind farm owners – as price-takers in the electricity market – suffer from these fluctuations, which tend to reduce revenue. To tackle these challenges, one emerging approach involves hybridizing the wind power plant (WPP) with other systems such as batteries [2, 3]. Operating such a hybrid power plant (HPP) in an optimal manner within the electricity market can help maximize profit while improving system reliability and stability.

An energy management system (EMS) facilitates the participation of HPPs in energy markets. State-of-the-art HPP-EMSs aim to maximize the overall revenue while utilizing battery energy storage (BES) to compensate for deviations from the optimal power reference, due to forecast errors and wind power variability [4, 5]. Such approaches fail to consider the cost of battery degradation, which may have a significant impact on the overall profit. Furthermore, some formulations use a simplified WPP model and BES degradation model [6, 7]. More recent and advanced HPP-EMS approaches do estimate battery damage more accurately, however, only an indirect damage minimization is typically considered and the cost of cyclic damage is approximated within the optimization [8].

The objective of this work is to develop a profit-optimizing EMS that 1) is based upon a data-driven generation and electricity price forecast model, and 2) considers directly and explicitly the cost of battery cyclic damage. An HPP controller (HPP-C) is formulated to ensure the fulfillment of the EMS optimal power reference. The HPP profit is quantified and the benefits due to the integration of measurement data and an improved optimization formulation are assessed and compared to state-of-the-art formulations. The deviation between HPP reference and generation is particularly crucial as it necessitates the deployment of grid ancillary services by the system operator, for which the HPP owner can be heavily penalized. In this context, another objective of this work is to assess the HPP tracking performances for different EMS optimization cases.

The remainder of the paper is organized as follows. Section 2 presents the underlying methodology developed in this work, explaining the HPP models in Sect. 2.1, the proposed data-driven forecasters for wind power and electricity market price in Sect. 2.2, mathematical formulation of profit-optimal EMS in Sect. 2.3, and the HPP controller in Sect. 2.4. The performance of the proposed EMS formulation is assessed through a simulation case study described in Sect. 3, followed by conclusions and outlook in Sect. 4.

2. Methodology

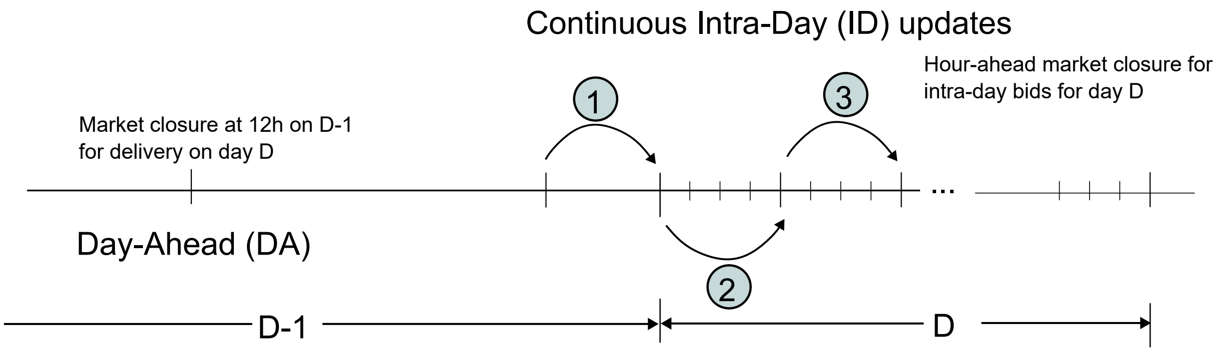

Figure 1: Energy market timeline for Germany.

A schematic representation of the energy market phases is shown in Fig. 1. The first bid opportunity, called 'day-ahead' (DA), takes place on the day before delivery, in hourly resolution. As the WPP generation forecast still has a high degree of uncertainty, the resulting deviations can later be corrected on the intra-day (ID) market, where market bidding takes place in a quarter-hourly resolution. It should be noted that the last opportunity for bid revision on the market occurs one hour ahead (HA) of the delivery time.

Figure 2 shows the considered setup in detail, where an HPP consisting of a WPP and a BES plant is connected to the electricity grid through a single point of interconnection. The HPP-EMS receives continuous updates on the market price, and the wind power forecasts, and calculates optimal power bids for the energy markets using HPP plant measurements. The HPP-C receives optimal power set-points from the HPP-EMS and ensures proper tracking.

2.1. Hybrid power plant

This section presents the characteristics of the wind power and battery plants that constitute the hybrid power plant considered in this work.

2.1.1. Wind power plant. The investigated wind farm consists of twelve 2 MW wind turbines in an irregular layout. All turbines have a rotor diameter of 82 m and a hub height of 80 m. The

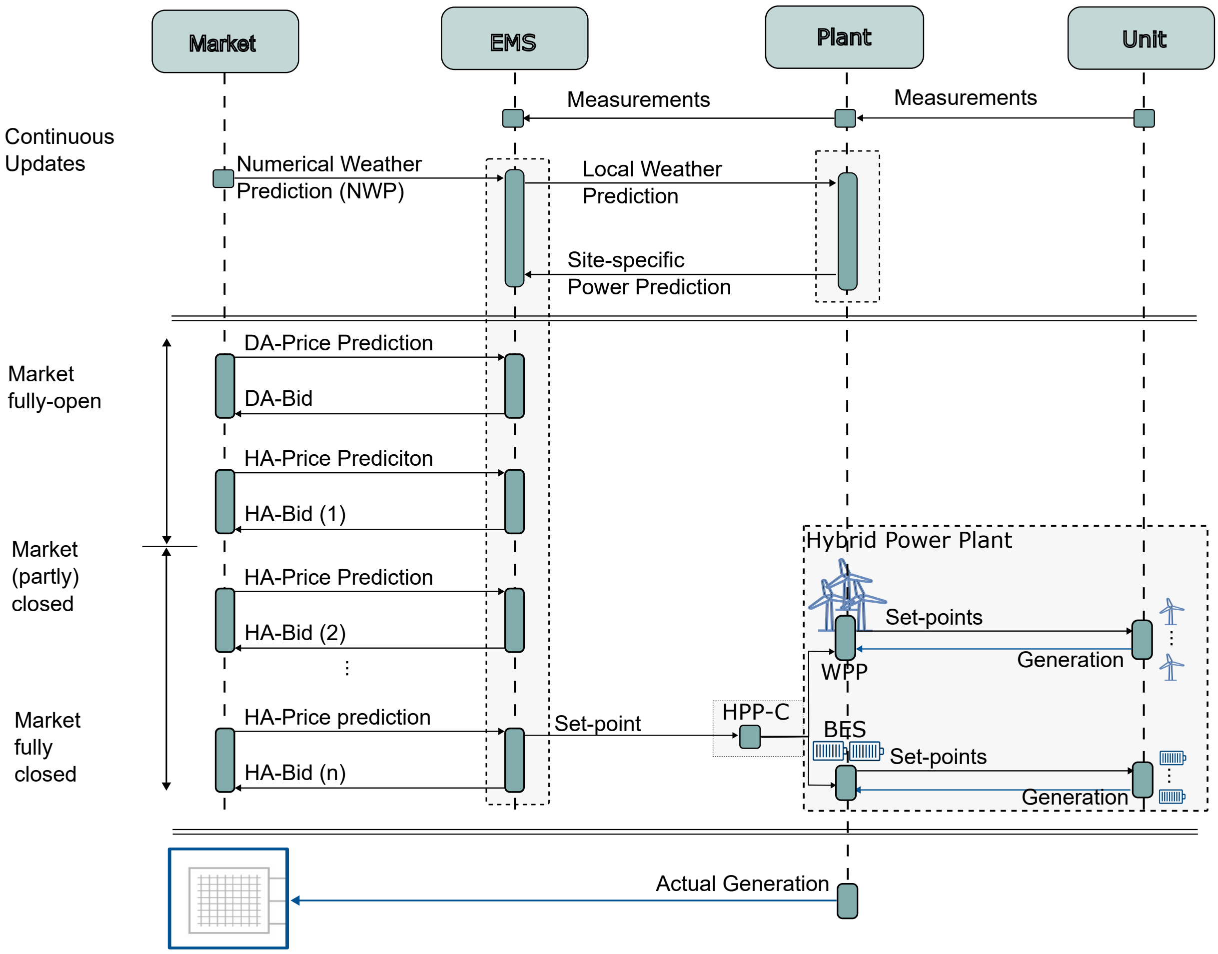

Figure 2: Schematic representation of participation of an HPP in an energy market.

site is characterized by gently rolling hills and can be characterized as semi-complex. The farm is located on a sloping terrain that slightly raises in elevation towards the southwest direction.

An engineering model is used to represent the effects of the flow within the wind plant [9]. The parameters of the farm flow model are tuned offline using site-specific measurement data, to better capture the wake interactions and accurately predict the power generation from individual turbines [10]. Two years of high-frequency on-site SCADA measurements, from 2019 to 2021, were utilized for the calibration process (see Sect. 2.2.2 for details).

2.1.2. Battery energy storage. An electrical equivalent circuit model of a 6 MW/6 MWh Li-ion battery has been considered in this work. The battery model consists of three sub-models: electrical, thermal, and degradation. For a given battery power P_B (positive for the discharging case and negative for charging one), the electrical sub-model captures the dynamics of the battery current I and the state of charge (SOC) as

$$S\dot{O}C = -\frac{I}{Q}. \tag{1}$$

Here, Q represents the maximum charge capacity of the battery at a given time and $(\dot{\ })$ indicates a derivative with respect to time. Q always decreases over time and usage because of the permanent loss in the capacity of the battery due to the accumulated cyclic damage Q_{cyc}. For a given set of SOC samples, Q_{cyc} is calculated with a novel Rainflow cycle-counting algorithm (refer to [11] for details), which explicitly considers the impact of SOC residue samples. The battery thermal model captures the dynamics of battery temperature T_b as

$$\dot{T_b} = \frac{1}{C_H}(I^2 R_{int} - C_R(T_b - T_{ambient})), \tag{2}$$

based on a lumped heat capacitance model [12], where C_R, C_H, and $T_{ambient}$ denote cooling rate, heat capacity, and ambient temperature, respectively. For the sake of simplicity, $T_{ambient}$ is assumed to be constant at 298.15K. The modeling approach of the BES has been discussed in detail in [13].

2.2. Forecasting

2.2.1. Wind condition forecast. The wind conditions are predicted using Deep Neural Networks (DNNs). The training targets are the north-aligned component u and the east-aligned component v of the wind measurements at the site for the next 36 hours. The choice of the forecast horizon of 36 hours is dictated by the application in the DA market, where the bidding stage for the DA stage (24-hour duration) closes 12 hours before the start of delivery. As input data, features from the two numerical weather prediction (NWP) models ICON-EU and ARPEGE are used [14, 15]. Additionally, lag features, i.e. the u and v component targets from previous timestamps were used for the input data. Instead of predicting the entire forecast horizon with a single DNN, an ensemble method consisting of multiple different DNNs is used. This is done by dividing the forecast horizon into 12 overlapping segments. For example, one segment covers hours 2 to 12, the next segment covers hours 4 to 16, and so on. The overlap is constructed so that each hour is covered by an ensemble of four DNNs. This approach was chosen because it leads to higher forecast accuracy in each segment, compared to the use of networks charged with forecasting over the entire horizon. For each step within the segments, the outputs of the four ensemble networks are averaged to produce the local forecast.

To reduce the number of input parameters of DNNs, a feature-selection algorithm is applied to each of the 12 DNNs, followed by a hyper-parameter optimization of the DNN architecture and the training optimizer. This automated hyper-parameter optimization step is based on parameter-exploring policy gradients (PGPE) [16]. The training was based on the Adam optimizer based on a mean squared error loss function [17]. The data was split into training (88%) and validation (12%) sets, avoiding correlations between the two.

2.2.2. Power generation forecast. The engineering flow model FLORIS uses the wind condition forecast to predict the inflow at each turbine as well as their individual power production [9]. As the baseline model does not capture all of the flow effects, a data-driven adaptation is used to reduce error and uncertainty in the power predictions. The adaptation is performed using historical measurement data, following the 'wind farm as a sensor' approach described in detail in [10].

Firstly, the methodology includes a re-calibration of the wake and turbulence model. The standard parameters of the Gaussian wake model and the Crespo-Hernandez wake-added turbulence model, were subject to retuning [18, 19]. The second correction is aimed at capturing terrain effects, which cause a heterogeneous background flow across the site. At present, the FLORIS version does not contain a terrain flow solver, and the site is assumed to be flat with homogeneous ambient flow. To correct for this, a heterogeneous field is modeled by means of a grid of flow speed-up nodes, whose parameter values are dependent on position and environmental conditions.

Historical measurement data is used to simultaneously learn the speed-up correction factors and to tune the wake model parameters. A maximum likelihood estimation finds the set of parameters that best describes the observed power output of the individual turbines. The wake model parameter-tuning resulted in a slightly slower wake decay, causing higher wake loss. The identified background wind speed field agreed with the terrain contour, with higher speed-ups towards the hill crest. The r.m.s.-error of turbine power prediction, normalized by rated power, is reduced from $\hat{\epsilon}_{\mathrm{T,rms}} = 0.084$ to 0.065, which corresponds to a 23% reduction for the validation data set.

2.2.3. Market price forecast The price forecasts for the energy market are based on DNNs. For both DA and ID price forecasts, historic data on Germany-wide renewable and non-renewable energy generation, total load, and import/export are used as input data for the DNN. During the training process, historic hourly DA auction prices are used as targets for the DA price forecast, while they also serve as additional input for the ID price forecaster. The ID forecaster aims to predict the quarter-hourly weighted average price of the preceding three hours before delivery (ID3). The normalized root mean square error (nRMSE) is used as a metric to evaluate the model accuracy during training for both price forecasters. Furthermore, a hyper-parameter optimization was also used (see Sect. 2.2.1).

2.3. Hybrid power plant: energy management system

The EMS receives continuous updates on the WPP generation forecast, market price forecast, as well as HPP system states, and participates in bidding stages of DA and ID markets. The EMS optimization problem aims to maximize the economic profit by balancing revenue accrued from selling electricity on the market and the cost of cyclic damage. The objective function can be mathematically written as

$$\max \sum_{t}^{T} \lambda_t^m \cdot b_t^m - C_t^{cyc} - w^{penalty} \cdot \mid \delta_t \mid . \tag{3}$$

The revenue on the current step m results from the market price forecast λ_t^m and the market bid b_m for each time interval t of the forecast horizon T.

The battery cyclic damage costs C_t^{cyc} are formulated using the Parameteric Online Rainflow Counting (PORFC) approach, which allows direct consideration and minimization of cyclic damage [11]. The PORFC algorithm uses a pre-processing step to identify fatigue cycles for a given set of SOC samples, and splits the respective damages over the contributing samples. The output of the pre-processing step is the PORFC mean parameters $SOC_{m,c}^{\mathrm{PORFC}}$ and PORFC weight parameters $SOC_{w,c}^{\mathrm{PORFC}}$ [13]. These parameters are used to obtain a continuous formulation of cyclic damage cost that can be written as

$$C_t^{cyc} = w_B \sum_{c=1}^{2} Q_{cyc,c,SOC}^{\mathrm{PORFC}} \left(SOC, SOC_{m,c}^{\mathrm{PORFC}}, SOC_{w,c}^{\mathrm{PORFC}} \right), \tag{4}$$

where the weight factor w_B represents the unit replacement cost of the battery [13].

The deviations between market biddings and HPP power generation δ_t are minimized through the penalty weight $w^{penalty} > 0$ and the soft-constraint

$$\delta_t = \sum_{m'} B_t^{m'} + b_t^m - p_t^{wpp} - p_t^{bess,res} \quad \forall\, t \in T. \tag{5}$$

The power generation of the HPP is determined by the combination of wind plant power p_t^{wpp} and the power from the battery storage $p_t^{bess,res}$, where the bids $B_t^{m'}$ on previous and already completed steps m' during ID stages are considered. While in the DA stage bids can be placed at any interval t, in the ID stage they are restricted to time intervals after the gate closure time t^{gc}, i.e.

$$b_t^m = 0 \quad \forall\, t \in T' = \{t \,|\, t \in T \wedge t \leq t^{gc}\}. \tag{6}$$

Battery storage within the EMS is modeled via the energy throughput approach,

$$SOC_{t+1} - SOC_t = -p_t^{bess,res} \cdot \frac{\Delta t}{C^{batt}} \quad \forall\, t \in T, \tag{7a}$$

$$p_t^{bess,res} = \frac{1}{\eta^{out}} \cdot p_t^{dch} - \eta^{in} \cdot p_t^{ch} \quad \forall\, t \in T, \tag{7b}$$

where SOC_t and C^{batt} represent state-of-charge and nominal capacity of the battery storage, η^{in} and η^{out} the charging and discharging efficiencies, p_t^{dch} and p_t^{ch} the charging and discharging power, and Δt the time difference between t and $t+1$.

Furthermore, the operation of the battery storage is restricted by the capacity limits for SOC and charging power,

$$0 \leq SOC_t \leq 1 \quad \forall\, t \in T, \tag{8a}$$

$$p_t^{dch} \leq p^{dch,max}, \quad p_t^{ch} \leq p^{ch,max} \quad \forall\, t \in T. \tag{8b}$$

The SOC is restricted to 50% for the initial and final state of the forecast horizon. Otherwise, during the intra-day market stage, the feedback of the electrical battery model (Sect. 2.1.2) is used to estimate the initial state $SOC_{0,est.}$ at the beginning of the remaining dispatch horizon, i.e.

$$SOC_{t_0} = \begin{cases} 0.5 & \text{if } t_0 = t_{init} \\ SOC_{0,est.} & \text{otherwise} \end{cases}, \tag{9a}$$

$$SOC_{t_{end}} = 0.5. \tag{9b}$$

The operation of the WPP is bounded by the forecasted power $p_t^{wpp,max}$, i.e.

$$0 \leq p_t^{wpp} \leq p_t^{wpp,max} \quad \forall\, t \in T. \tag{10}$$

2.4. Hybrid power plant: controller

The inevitable short-term forecast errors are compensated, post-market-closure, using wind farm curtailment and/or battery reserves. As a consequence, HPP-C is formulated as a rule-based controller that, depending on wind farm availability, decides to either curtail the wind farm or generate the available power. The remaining power goes as a reference to the battery, depending on the battery current SOC, to ensure fulfillment of the HPP reference.

As HPP power tracking is of key importance to maximize performance, the implementation of WPP power tracking is based here on a margin-boosting wind farm active power controller (APC), which reduces the occurrence of saturation events of individual turbines [20]. The method combines wake control with induction control, where improved tracking performance is achieved by explicitly maximizing the power margin to hedge against wind lulls. The core of control architecture is a model-based optimal planner for the open-loop set-point of the individual turbines. This is combined with a closed-loop corrector to ensure optimal tracking.

The battery controller is formulated as a rule-based controller that checks if the desired power can be provided by the BES, depending on the current SOC. If the available power is greater than the desired power, the battery fulfills the set-point. Otherwise, the battery provides the set-point power only until it reaches the prescribed SOC limit.

3. Case study

To evaluate the proposed HPP-EMS, a simulation case study has been performed, where the considered HPP (refer to Sect. 2.1 for details) is participating in the German energy market for 72 hours in March 2019. The optimal HPP power reference and corresponding share of WPP that optimizes the EMS objective are dispatched to the HPP-C every 15 minutes. The HPP-C is executed every minute and the battery SOC update is sent back to the EMS. The case study, including the communication between individual blocks, is implemented using the digital twin framework *MesH-REcon*, which is presented in detail in [21].

Three HPP-EMS formulations have been compared. The first is built upon the current industry standards (henceforth referred to as *standard*), where the EMS utilizes wind power predictions based on the NWP models and aims to maximize HPP revenue. The second case (henceforth referred to as *standard+data*) has an improved power forecasting ability due to the integration of site-specific measurements, but still aims to maximize only revenue. These two cases are compared with the proposed formulation (henceforth referred to as *proposed*), where EMS uses data-driven wind condition forecasting combined with a tuned wind farm model to obtain wind power predictions, and maximizes HPP profit by balancing the revenue accrued from the market and the cost of battery cyclic damage. All three cases use BES to compensate for short-term deviations. Tab.1 summarizes the characteristics of different HPP-EMS formulations assessed in this section.

Table 1: Characteristics of assessed HPP-EMS formulations

Case	Wind condition forecast	Power generation forecast	HPP-EMS objective
standard	Numerical weather prediction	standard wake model	Maximize revenue
standard+data	Deep neural networks	tuned wake model	Maximize revenue
proposed	Deep neural networks	tuned wake model	Maximize profit

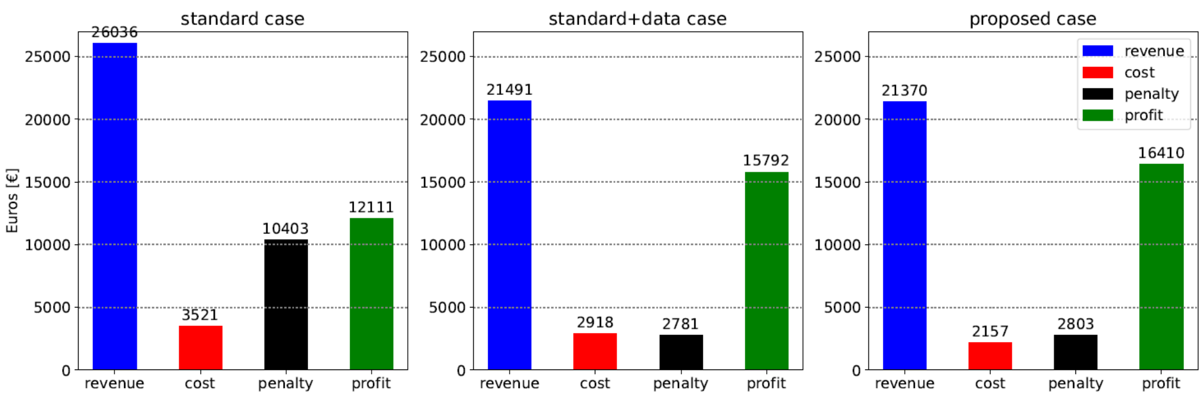

Figure 3: Economic performance of the HPP participation in the German energy market.

Figure 3 shows the economic performance of the HPP for the three EMS formulations. The net economic profit (shown in green) is calculated as the difference between revenue, cost, and penalty. Revenue (shown in dark blue) is calculated as the product of power bids and respective actual prices for both the DA and ID markets. Cost (shown in red) is calculated as the fraction of the replacement cost of the battery due to the accumulated cyclic degradation. Penalty (shown in black) is calculated as the product of HPP generation error and balancing energy ($reBAP$) price. The *proposed* formulation results in a 35.5% higher net profit than the *standard* formulation. The results for *standard+data* formulation show that just the effective integration of site-specific measurements results in a 30.1% higher profit. Thus, an additional 5.4% improvement is due to a direct and accurate consideration of the cost of battery damage within the EMS optimization.

Figure 4: Dynamic performance of the HPP participating in the energy market.

Figure 4 shows the bid (in dashed line), set-point (in dotted line), and the actual generation (in solid line) of the HPP for the three EMS formulations as three subplots. The bid curve represents the bid cleared by the market. Post-market closure and before the time of power delivery, the EMS still modifies the HPP set-point based on the most recent update of the wind power forecast and the battery SOC. Figure 4 shows that, for the *standard* formulation, the EMS foresees a significantly higher generation capacity compared to the other two cases and hence bids more in the market. However, the generation error is also significantly higher, owing to the inferior forecasting accuracy of the NWP models that do not capture site-specific weather phenomena as well as local terrain effects. For the *standard+data* and *proposed* formulations, a more accurate forecast of wind power production results in a more precise power bid and considerably reduced errors between set-point and actual generation. As a consequence, both the revenue and penalty are significantly smaller, resulting in a higher overall profit than the *standard* formulation, as seen in Fig. 3.

As mentioned previously, once the set-point is sent to the HPP-C, the energy stored in BES is used to compensate for short-term deviations. Since in the *proposed* formulation, the EMS explicitly considers the damage due to SOC cycles and balances it against the market revenue, the EMS bids slightly less power in the market, leading to smaller revenues. Figure 5 shows the resulting SOC profile for the three formulations. Results indicate that both the *proposed* and the *standard+data* formulations are characterized by fewer cycles of smaller cycle depth, whereas the *standard* formulation is characterized by multiple cycles of larger depth. This is because of the increased short-term compensation that is required in this case by using battery reserves. Moreover, the cycle depth of the *proposed* formulation is smaller than the one of the *standard+data* formulation. This is because of the explicit minimization of cyclic damage within the EMS optimization, which results in the lowest cost of cyclic damage for the *proposed* formulation. Furthermore, the reduction in the cost of BES damage is achieved at a

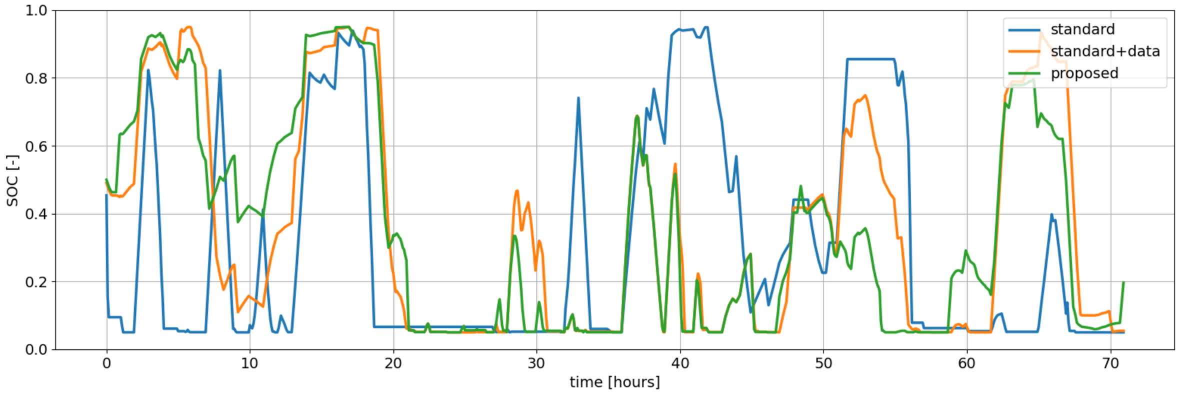

Figure 5: State of charge profile showing the utilization of BES for the three EMS formulations.

similar penalty as in the *standard+data* case, leading to the highest net profit for the *proposed* formulation.

4. Conclusions

In this work, an EMS is formulated for an HPP participating in bidding stages in the German energy market. The HPP utilizes site-specific historical measurements to improve wind power forecasts. Additionally, it uses an online cyclic damage minimization approach to accurately balance the battery damage cost against the revenue obtained by selling electricity on the market. The *proposed* formulation is compared to an industry *standard* formulation, and to an intermediate *standard+data* formulation.

Although the *standard* case generates the highest revenue, because of its forecast error the deviation penalties are significantly higher, resulting in a smaller profit. The integration of site-specific data in the *standard+data* case shows a significant reduction in deviation penalties, but only a slightly smaller battery degradation cost, highlighting the role of battery reserves in mitigating deviations. In the *proposed* case, the optimizer is empowered by a more accurate information on battery degradation and by a reduced forecasting uncertainty, resulting in the highest economic profit.

Future extensions of this work include replacing the current deterministic power and market price forecasts with probabilistic ones, and performing a stochastic optimization within the EMS. Furthermore, it would be interesting to assess the impact of different wind farm control power tracking approaches on the HPP economic performance.

5. Acknowledgements

The authors express their gratitude to Mr. Benjamin Dittrich and Mr. David Coimbra from EnergieKontor AG, who granted access to the field data and supported this work. The work has been supported by the e-TWINS project (FKZ: 03EI6020), which receives funding from the German Federal Ministry for Economic Affairs and Climate Action (BMWK). This work has also been partially supported by the SUDOCO project, which receives funding from the European Union's Horizon Europe Programme under the grant agreement No. 101122256.

References

[1] Weihao Hu, Zhe Chen, and Birgitte Bak-Jensen. "The Relationship Between Electricity Price and Wind Power Generation in Danish Electricity Markets". In: (), pp. 1–4. DOI: 10.1109/APPEEC.2010.5448739.

[2] Haoran Zhao et al. "Review of energy storage system for wind power integration support". In: *Applied Energy* 137 (2015), pp. 545–553. ISSN: 03062619. DOI: 10.1016/j.apenergy.2014.04.103.

[3] Katherine Dykes et al. "Opportunities for Research and Development of Hybrid Power Plants". In: (). DOI: 10.2172/1659803.

[4] Kaushik Das et al. "Optimal battery operation for revenue maximization of wind-storage hybrid power plant". In: *Electric Power Systems Research* 189 (2020), p. 106631. ISSN: 03787796. DOI: 10.1016/j.epsr.2020.106631.

[5] Q. Long et al. "Interfacing energy management with supervisory control for hybrid power plants". In: (), pp. 347–351. DOI: 10.1049/icp.2021.2634.

[6] Xinsong Zhang et al. "On Generation Schedule Tracking of Wind Farms With Battery Energy Storage Systems". In: *IEEE Transactions on Sustainable Energy* 8.1 (2017), pp. 341–353. ISSN: 1949-3029. DOI: 10.1109/TSTE.2016.2598823.

[7] Fengji Luo et al. "Coordinated Operational Planning for Wind Farm With Battery Energy Storage System". In: *IEEE Transactions on Sustainable Energy* 6.1 (2015), pp. 253–262. ISSN: 1949-3029. DOI: 10.1109/TSTE.2014.2367550.

[8] Rujie Zhu et al. "Optimal Participation of Co-Located Wind–Battery Plants in Sequential Electricity Markets". In: *Energies* 16.15 (2023), p. 5597. DOI: 10.3390/en16155597.

[9] NREL. *FLORIS. Version 3.2.* 2022.

[10] Robert Braunbehrens, Andreas Vad, and Carlo L. Bottasso. "The wind farm as a sensor: learning and explaining orographic and plant-induced flow heterogeneities from operational data". In: *Wind Energy Science* 8.5 (2023), pp. 691–723. DOI: 10.5194/wes-8-691-2023.

[11] Abhinav Anand, Stefan Loew, and Carlo L. Bottasso. "Economic nonlinear model predictive control of fatigue for a hybrid wind-battery generation system". In: *Journal of Physics: Conference Series* 2265.3 (2022), p. 032106. ISSN: 1742-6596. DOI: 10.1088/1742-6596/2265/3/032106.

[12] Zuchang Gao et al. "Integrated Equivalent Circuit and Thermal Model for Simulation of Temperature-Dependent LiFePO4 Battery in Actual Embedded Application". In: *Energies* 10.1 (2017), p. 85. DOI: 10.3390/en10010085.

[13] Stefan Loew, Abhinav Anand, and Andrei Szabo. "Economic model predictive control of Li–ion battery cyclic aging via online rainflow–analysis". In: *Energy Storage* 3.3 (2021). ISSN: 2578-4862. DOI: 10.1002/est2.228.

[14] Günther Zängl et al. "The ICON (ICOsahedral Non–hydrostatic) modelling framework of DWD and MPI–M : Description of the non–hydrostatic dynamical core". In: *Quarterly Journal of the Royal Meteorological Society* 141.687 (2015), pp. 563–579. ISSN: 0035-9009. DOI: 10.1002/qj.2378.

[15] P. Courtier et al. "The Arpege project at Meteo France". In: *Seminar on Numerical Methods in Atmospheric Models, 9-13 September 1991* II ().

[16] Frank Sehnke et al. "Parameter-exploring policy gradients". In: *Neural networks : the official journal of the International Neural Network Society* 23.4 (2010), pp. 551–559. DOI: 10.1016/j.neunet.2009.12.004.

[17] Diederik P. Kingma and Jimmy Ba. "Adam: A Method for Stochastic Optimization". In: (). DOI: 10.48550/arXiv.1412.6980.

[18] Majid Bastankhah and Fernando Porté-Agel. "A new analytical model for wind-turbine wakes". In: *Renewable Energy* 70 (2014), pp. 116–123. ISSN: 09601481. DOI: 10.1016/j.renene.2014.01.002.

[19] A. Crespo and J. Herna´ndez. "Turbulence characteristics in wind-turbine wakes". In: *Journal of Wind Engineering and Industrial Aerodynamics* 61.1 (1996), pp. 71–85. ISSN: 01676105. DOI: 10.1016/0167-6105(95)00033-X.

[20] Simone Tamaro and Carlo L. Bottasso. "A New Wind Farm Active Power Control Strategy to Boost Tracking Margins in High-demand Scenarios". In: *2023 American Control Conference (ACC)* (2023), pp. 192–197. DOI: 10.23919/ACC55779.2023.10156275.

[21] Zhao Song et al. "Digital Twins for the Future Power System: An Overview and a Future Perspective". In: *Sustainability* 15.6 (2023), p. 5259. DOI: 10.3390/su15065259.