HyDesign: a tool for sizing optimization for grid-connected hybrid power plants including wind, solar photovoltaic, and Li-ion batteries

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Abstract. Hybrid renewable power plants consisting of collocated wind, solar photovoltaic (PV) and Lithium-ion battery storage connected behind a single grid connection can provide additional value to the owners and to society in comparison to individual technology plants such as only wind or only solar-PV. These benefits become significant in projects that have requirements to supply a certain amount of energy during peak hours given a set of grid capacity constraints or when the plant is selling the electricity with time-varying electricity prices. The hybrid power plants considered in this article are connected to the grid and share electrical infrastructure costs across the different generation and storing technologies. In this article, we propose a methodology for sizing of hybrid power plants as an optimization problem that maximizes the net present values over capital expenditures and compares it with standard designs that minimize the levelized cost of energy. The sizing problem formulation includes turbine selection (in terms of rated power, specific power and hub height), a wind plant wake losses surrogate, simplified photo-voltaic panel degradation, an internal energy management system operation optimization and battery degradation. The multi-disciplinary optimization problem is solved using a new parallel "efficient global optimization" algorithm. This new algorithm is a surrogate-based optimization method that ensures a minimal number of model evaluations but ensures a global scope in the optimization. The methodology presented in this article is available in an open-source tool called HyDesign. The hybrid sizing algorithm is applied for a peak-power plant use case at different locations in India where the renewable energy auctions impose a monetary penalty when energy is not supplied at peak hours.

1 Introduction

Hybrid power plants (HPP) consisting of collocated wind, solar photovoltaic (PV) and Lithium-ion battery storage connected behind a single grid connection point can provide better returns of investment than individual source (wind or solar) plants in locations where the wind and solar resources are comparable and for electricity markets in which fixed power purchase agreement electricity prices are not possible. HPP can be designed to have operational flexibility in terms of dispatchability and ancillary service provision that makes them closer to traditional power plants in terms of achieving additional profitability in markets with time-varying electricity prices under grid connection constraints and that have reduced costs due to the shared infrastructure (Gorman et al., 2020; Dykes et al., 2020).
Sizing of HPP plant is a multi-discipline analysis and optimization (MDAO) problem that requires detailed modeling of the wind and solar resources as well as the wind, PV and storage performance, costs and operation (Dykes et al., 2020). Additionally, the selection of the wind turbine characteristics (specific power, hub height) and PV characteristics (panel orientation) are additional degrees of freedom that can significantly modify the results of the sizing. Traditional objective functions of the sizing optimization problem are maximizing net annual energy production or minimizing levelized cost of energy (LCoE) (Tripp et al., 2022), but in general HPP designs that include energy storage can produce more revenues relative to the cost increase. In this article, we compare HPP sizing optimization for both LCoE and relative net revenues as objective functions.

A detailed energy management system (EMS) is required to determine the operation of the battery given the time-series of wind and solar generation and the battery’s capacity. EMS optimization will determine when to charge and discharge the battery with the objective of maximizing the revenue obtained by the HPP. Several articles focus on formulating EMS optimization problems and propose different formulations Al-Lawati et al. (2021); Das et al. (2020); Khaloie et al. (2021a, b); Wang et al. (2019). Different levels of complexity can be studied in the implementation of EMS such as: (1) rule-base algorithms that prescribe the operation of the battery, (2) deterministic EMS optimization that maximizes the revenues assuming perfect forecasts (full future-knowledge) on the price of electricity, the wind and solar generation time-series, (3) robust optimization of EMS operation will provide battery operation under worst case scenarios of forecast errors of generation and prices time-series, and (4) Stochastic optimization of EMS operation that will provide best operation over the entire distribution of forecasting error. EMS operational optimization within the HPP sizing optimization is not common in the literature but it is required in order to unravel the value of hybrid plants fully.

Furthermore, HPP sizing requires solving the long-term performance of the different components through the lifetime of the HPP project; this implies modeling the degradation in the performance of the individual components. Li-ion batteries and PV cells have significant degradation over time, several models of degradation exist (Jordan et al., 2016), while wind turbine is assumed not to have significant performance degradation since the internal wind turbine pitch control system will ensure that the rated power and performance of the turbine is kept approximately constant over its lifetime.

Typically, battery cells have to be replaced when their capacity degrades beyond a pre-defined threshold. The higher CAPEX of new batteries plays a dominant role in battery operation cost, i.e. degradation cost. Therefore, considering battery degradation when sizing HPP can optimize the use of battery and hence extend battery lifetime and reduce costs. Battery degradation is a complicated chemical process. Theoretical studies (Safari et al., 2008; Vetter et al., 2005) on battery degradation explains the detailed degradation mechanism of battery cells. However, the required parameters and conditions of the battery cell can not be obtained in the sizing stage. To incorporate the battery degradation model into the sizing problem, it is possible to use semi-empirical models (Xu et al., 2016) that only require the state of charge time-series (SoC) as input to assess battery lifetime. This model considers the solid electrolyte inter-phase film formation theory calibrated based on experimental observations and it is able to describe the non-linear degradation process.

To the authors’ knowledge, there is no available sizing methodology for the design of utility-scale grid-constrained hybrid power plants considering all the above-mentioned characteristics. This article presents a general methodology for hybrid plant sizing as a MDAO including several novel aspects: (1) turbine selection (2) PV degradation (3) battery degradation (4) internal
EMS operation optimization. We apply the methodology and report the detailed result of the hybrid plant design in three different locations in India: (a) solar dominant site (b) wind dominant site and (c) low wind and solar resources.

India is a large market in which hybrid plants could become important because of the need to provide renewable energy that supports the demand patterns and because of the intermediate solar and wind resources. For this reason, Indian sites are used as example cases in this article.

2 Methodology

The design of a HPP is an optimization problem that involves several sub-optimization problems such as: wind turbine selection, siting and layout optimization, PV array siting, energy management system (EMS) operation optimization coupled with battery degradation and electrical infrastructure optimization. Early HPP sizing optimization focused on maximizing the viability of a HPP installation in a given location requires a simplified approach. The XDSM diagram of the HPP sizing optimization problem is presented in figure 1. In the sizing optimization several simplifications are performed in order to reduce the complexity of the optimization: (1) the WT Layout optimization is replaced by a surrogate of the wakes of sub-optimal wind turbine layouts, (2) uncoupled battery and PV degradation models reduce the complexity of the EMS optimization, a short-term EMS optimization problems is proposed that considers a constrain in battery utilization, while a long-term operation rule-based EMS corrects the ideal operation for degradation, (3) approximate electrical infrastructure costs are used.

Figure 1. HPP sizing XDSM diagram.
2.1 Generic Wind Turbine

A look-up table is built based on DTU’s pywake generic turbine model (Pedersen et al., 2023). The interpolation of this data is a surrogate that predicts the power and thrust coefficient curves given the turbine’s specific power, defined as the ratio between the rated power and the rotor area \( sp = \frac{P_{\text{rated}}}{A} \). The wind turbine power curve and thrust coefficient curves are represented as \( P_{WT}(WS) \) and \( C_T(WS) \) in figure 1. Examples of the surrogate power and thrust coefficient curves are given in figure 2.

![Figure 2. Generic Wind Turbine surrogate.](image)

2.2 Generic Wind Power Plant Wake Model

A database of wind power plants is generated using circular plant borders and a simplified layout optimization that maximizes the distance between the turbines. Two example layouts are presented in figure 3. Wakes are simulated using pyWake’s implementation of Zong’s wake model (Pedersen et al., 2023; Zong and Porté-Agel, 2020) which combines a Gaussian wind speed deficit with local turbulence dependent linear wake expansion, with squared sum wake deficit superposition model and Frandsen’s added turbulence model as specified in the IEC wind turbine design standard (Commission et al., 2017).

Detailed wake losses as a function of wind speed and wind direction are simulated for multiple WPP layouts with the same number of turbines and installation density \( \rho_W \), plant-rated power over the land use area, \([\text{MW/km}^2]\)) for a given turbine’s specific power. The results are aggregated taking the 90-th larger quantile wake losses across wind directions and across 20 layouts generated using a different random seed number. A surrogate of the wake losses curve \( WL(WS) \) is built as a function of the installation density, number of turbines and specific power of the turbine. Example results of the surrogate are presented in Figure 4. Finally, the generic wind plant model will combine the turbine power curve with the expected wake losses to provide a wake-affected plant power curve, see equation 1.

\[
WL(WS) \approx \hat{WL}(N_{WT}, sp, \rho_W, WS)
\]

\[
P_W(WS) = P_{WT}(WS) \times (1 - WL(WS))
\]

(1)
Figure 3. WPP example of generated layouts.

Figure 4. Example wake losses as a function of the number of turbines, installation density [MW/km²] and turbine’s specific power.
2.3 Weather

ERA5 (Hersbach et al., 2020) is used as a reanalysis dataset for wind resource calculations. The hourly wind velocity time-series with a 0.25x0.25 degree resolution in latitude and longitude are interpolated into heights of 50, 100, 150 and 200 [m]. This dataset is stored and interpolated at the location of hybrid power plant using linear interpolation in the horizontal coordinates, keeping the hub height dimension of the velocities in order to compute the effect of changing the hub height of the turbines in the optimization.

The mean wind speed from the Global Wind Atlas 2 (GWA2) is used for correcting ERA5’s mean wind speed following the approach presented in (Murcia et al., 2022). This scaling correction is necessary in order to include the first order effects of terrain. The corrected wind speed time-series is provided on multiple heights ($WS(y, t)$) to the atmospheric boundary layer (ABL) model. This model uses a piece-wise power law interpolation to determine the wind speed time-series at hub height ($WS_{hh}(t)$).

ERA5-land is used as a reanalysis of the hourly global horizontal irradiance time-series ($GHI(t)$) because it has a better resolution than ERA5, 0.1 degrees versus 0.25 degrees in latitude and longitude resolution, and it shows a better validation metrics for individual plant modeling (Camargo and Schmidt, 2020). Decomposition of GHI to direct normal irradiance (DNI) and diffuse horizontal irradiance (DHI) is done in two steps: the DISC model is used to estimate the DNI (Maxwell, 1987) using the GHI and relative air mass model based (Kasten and Young, 1989). While the DHI is estimated using the solar position, see equation 2.

$$DHI(t) = GHI(t) - DNI(t) \times \cos(\theta_{zenith}(t)) \tag{2}$$

2.4 Wind power plant model (WPP)

The wind generation time-series ($W(t)$) is obtained by interpolating the plant power curve at the hub height’s wind speed time-series, scaling the generation by the installed capacity. Additionally, an efficiency ($\eta_W = 0.95$) is assumed to cover the electrical and availability losses, see equation 3.

$$W(t) = N_{WT} \times P_{rated} \times P_W(WS_{hh}(t)) \times \eta_W \tag{3}$$

2.5 PV power plant model (PVP)

Power conversion uses PVLib (Holmgren et al., 2018) based on a generic 1MW PV plant configuration (PV module, inverter and open rack with glass-glass) with the irradiance projection transposition model (Davies and Hay, 1978), the Sandia array performance model (SAPM) (King et al., 2004) and Sandia performance model for grid-connected PV-inverter model (King et al., 2007). The final solar PV generation requires the plant capacity, the orientation of the panels in terms of tilt and azimuth angles ($\theta_{tilt}, \theta_{azim}$), the ratio between DC and AC sides of the inverter ($C_{S_{inverter}}$), the irradiances (DNI, DHI), the wind speed close to ground ($WS_1(t)$) and the ambient temperature ($T_1(t)$), see equation 4.
\[ S(t) = S_{MW} \ast PV(\theta_{tilt}, \theta_{azim}, r_{DC-AC}, DNI(t), DHI(t), WS_1(t), T_1(t)) \]  

(4)

The PV degradation model is a linear loss of capacity lost over the lifetime given a degradation per year (default value of 0.5% per year).

2.6 Electricity price

The electricity price time-series in the Spot market \((Pr(t))\) is an input to the model, note that the price time-series need to be correlated with the weather time-series. This report focuses on valuation of time varying power purchase agreements as the ones that have been seen in the Indian HPP market. This price signals has two levels of electricity price at peak and non-peak (demand) hours. An example of the peak non-peak PPA electricity price is presented in figure 5.

2.7 Energy management system optimization model (EMS)

The energy management system optimization model consists in selecting the amount of battery charge/discharge and power curtailment that maximizes the revenue generated by the plant over a period of time (usually one or two years), including a possible penalty for not meeting the requirement of energy generation and a penalty for battery power ramping to control the amount of battery degradation, see equation 5. Note that the EMS optimization is solved using linear programming and therefore does not compute the battery degradation, instead, it assumes new battery and PV panels (without degradation). The idealized EMS operation design also assumes perfect knowledge of both the weather and price, and therefore there are neither forecasting errors on the prices nor weather.

The revenue is given by the product of electricity price \((Pr(t))\) and the HPP power generation \((H(t))\) minus the penalty over the period \((l)\) and minus the battery ramping penalty \((l_b)\). The HPP generation is defined as the total power from wind \((W(t))\), solar PV \((S(t))\), battery charge or discharge \((B(t))\) and power curtailment \((P_{curt}(t))\).

The penalty \((l)\) is the missing energy generated at peak times with respect to the energy requirement over the period \((E_l)\) times a mean peak electricity price \((Pr(t_{peak}))\). The penalty can only be positive, which means that it can only subtract revenue, and not give extra revenue to generate above the requirements.

The battery fluctuations penalty \((l_b)\) is defined as the sum of the products of the absolute battery power fluctuations \((|\Delta B(t)|)\) and the difference between max electricity price and the current price \((Pr_{max} - Pr(t))\). This means that large fluctuations in the battery charge/discharge are allowed when the price is high. The battery fluctuation penalty factor \((C_{bfl})\) is a design variable that captures how strongly can the battery be ramped and therefore it controls the battery degradation, when \(C_{bfl}\) is 0 then large changes in charge/discharge occur, see figure 5.

The constraints in the optimization keep track of battery level \((E_{SOC}(t))\), enforcing the batteries energy \((B_E(t))\) and power capacity \((B_P)\), force the grid constraints, including an asymmetric charging/discharging efficiency \((\eta_{charge}, \eta_{discharge})\), a minimum level of battery discharge \((B_{Edepth})\).
\[
\text{max} \sum_t (Pr(t) \times H(t)) - l - l_b
\]

with
\[
l = \begin{cases} 
E_l \times Pr(t_{\text{peak}}) & \text{if } E_l > 0 \\
0 & \text{if } E_l \leq 0 
\end{cases}
\]

\[
E_l = (E_{\text{peak req}} - \sum_{t \in t_{\text{peak}}} (H(t) \Delta t))
\]

\[
l_b = C_{bfl} \times \sum_t |\Delta B(t)| \times [Pr_{\text{max}} - Pr(t)]
\]

such that \( \forall t \) \( H(t) = W(t) + S(t) + B(t) - P_{\text{curt}}(t) \)

\[H(t) \leq G\]

\[E_{\text{SOC}}(t + 1) = \begin{cases} 
E_{\text{SOC}}(t) - \eta_{\text{charge}} B(t) \Delta t & \text{if } B(t) \leq 0 \\
E_{\text{SOC}}(t) - B(t) \Delta t / \eta_{\text{discharge}} & \text{if } B(t) \geq 0 
\end{cases}\]

\[E_{\text{SOC}}(t) \geq B_E(t) \times [1 - B_{E,\text{depth}}]\]

\[E_{\text{SOC}}(t) \leq B_B(t)\]

\[B(t) \leq B_P\]

\[B(t) \geq -B_P\]

---

**Figure 5.** EMS comparison in an example HPP for two different battery fluctuation penalty factor \( C_{bfl} \).
2.8 Battery degradation model

The battery degradation model includes the linear degradation rate regarding cycle numbers and the non-linear degradation due to the solid electrolyte interphase film formation process in the early stage of the battery life. A rainflow counting (Downing and Socie, 1982; Shi et al., 2018) is implemented to obtain the depth of discharge ($R_{DoD}$), mean state of charge cycle ($R_{SoC}$), half or full cycle count ($R_{count}$), for a number of cycle frequencies ($n_R$) given a state of charge time-series ($E_{SOC}(t)$).

The linear degradation rate ($f_d$) in equation 6 depends on a stress model due to the depth of discharge ($S_{DoD}(R_{DoD})$), a stress model due to cycle count and age of the battery ($S_{t}(R_{count}, t_c)$), a stress model due to state of charge ($S_{SoC}(R_{SoC})$), and a stress model due to cell temperature ($S_{T}(T_c)$). The stress factor models are empirical relationships calibrated on measurements (Xu et al., 2016).

$$f_d = \sum_{j=1}^{n_R} [S_{DoD}(R_{DoD,j}) + S_{t}(R_{count,j}, t_c)] \times S_{SoC}(R_{SoC,j}) S_{T}(T_c)$$  \hspace{1cm} (6)

The non-linear part of the degradation given in Eq. 7 calculates the loss of storing capacity (LoC, $L$) using two models: fresh battery and used battery after the formation of SEI film. A pre-defined LoC level is used to determine in which regime is the battery ($L_1$). $L'$ and $f_d'$ are the LoC and linear estimation of LoC when $L$ exceeds $L_1$ at the first time. Where the parameters of the model take the following values $\alpha = 0.0575$ and $\beta = 121$.

$$L = \begin{cases} 
1 - \alpha e^{-\beta f_d} - (1 - \alpha)e^{-f_d} & \text{if } L \leq L_1 \\
1 - (1 - L') e^{-f_d} + f_d' & \text{if } L > L_1 
\end{cases}$$  \hspace{1cm} (7)

Finally, the remaining energy capacity of the battery $B_{E}$, is the remaining of loss factor of the original energy storing capacity: $B_{E}(t) = B_{E,new} \times [1 - L(t)]$. In this article, the battery degradation model is not coupled to the EMS model, but instead it uses the resulting state of charge time-series ($SoC$) estimated by the EMS optimization on an operation period (for example one or two years). The SoC operation period is repeated to have a full lifetime of operation to compute the degradation over the lifetime of the HPP. The continuous degradation curve is discretized in periods of constant health levels in order to simplify the implementation of the long-term operation correction. Finally, battery replacement occurs when the battery reaches a minimum health level (70%), see Figure 6.
2.9 Long-term operation: Rule-based Energy management system correction model (EMS Long-term)

A ruled based EMS is implemented in order to account for battery degradation, degradation in PV and forecast errors in estimated wind and solar generation without having to run new EMS optimizations. The correction model consists in the following general principles: (1) try to follow the ideal EMS operation if possible, (2) update the state of charge to account for reduction in the available generation in the HPP and the new limits of the degraded battery, (3) recompute the battery power operation and HPP curtailment accounting for the charge and discharge efficiencies.

The implementation consist in estimated the reduction in charging power due to the different available generation and curtailment ($B_{LT}(t)$) as presented in equation 8, update the SOC ($E_{SOC-LT}(t)$) including the constraints of the new energy limits of the battery, equation 9, and finally recompute the battery power ($P_{Bp}$) to supply the SOC and curtailment ($P_{curt-LT}(t)$), equation 10:

\[
P_{loss}(t) = \max(H(t) - H_{act}(t) - P_{curt}(t), 0)
\]

\[
B_{LT}(t) = \min(B(t) + P_{loss}(t), 0) \quad \text{if} \; B(t) < 0
\]

\[
B_{LT}(t) \leq B_P
\]

\[
B_{LT}(t) \geq -B_P
\]

\[
E_{SOC-LT}(t+1) = \begin{cases} 
E_{SOC-LT}(t) - \eta_{charge} B_{LT}(t) \Delta t & \text{if} \; B_{LT}(t) \leq 0 \\
E_{SOC-LT}(t) - B_{LT}(t) \Delta t/\eta_{discharge} & \text{if} \; B_{LT}(t) \geq 0 
\end{cases}
\]

\[
B_{LT}(t) \leq B_E(t) \times [1 - B_{E_depth}]
\]

\[
E_{SOC-LT}(t) \leq B_E(t)
\]
\[ B_{LT}(t) = \begin{cases} 
\frac{(E_{SOC}-LT(t) - E_{SOC}-LT(t+1))}{\eta_{charge} \Delta t} & \text{if } E_{SOC}-LT(t) - E_{SOC}-LT(t+1) \leq 0 \\
\frac{(E_{SOC}-LT(t) - E_{SOC}-LT(t+1))}{\Delta t / \eta_{discharge}} & \text{if } E_{SOC}-LT(t) - E_{SOC}-LT(t+1) \geq 0 
\end{cases} \]

\[ P_{curt-LT}(t) = \max(H_{act}(t) + B_{LT}(t) - G, 0) \]

\[ H_{LT}(t) = H_{act}(t) - P_{curt-LT}(t) + B_{LT}(t) \]

(10)

A comparison of the two versions of EMS is presented in Figure 7 for 500 different sizing capacities and levels of degradation in 12 example locations (the 3 Indian example locations discussed in this article, and 3 locations in France, UK and Germany each one of them using a time-varying Spot electricity price), a total of 6000 single year operations were run. It can be seen that the rule-based EMS-LT correction is able to predict the revenue \((P r(t) H(t))\) generated when the HPP is operating with degradation. Even though there is bias in the relative error shown in a median of 1.4%, a 25% quantile of 0.4% and a 75% quantile of 2.9%, most of the cases (within the 5% and 95% quantiles) have relative errors are between 0.0% and 5.8%.

![Figure 7](https://doi.org/10.5194/wes-2023-83)

**Figure 7.** Cross-validation errors on rule.

### 2.10 Wind plant costs model

A simple WPP cost model consist in estimating the total capital expenditure costs (CAPEX, \(C_W\)) and operational and maintenance costs (OPEX, \(O_W\)) as a function of the installed capacity (given as number of turbines times the rated power of the turbines: \(W_{MW} = N_{wt} P_{rated}\)), the cost of the turbines, their construction and civil infrastructure (\(C_{WT}+C_{W\text{ civil}}\)). The OPEX is divided into fixed costs that scaled with the rated capacity of the plant (\(O_{W\text{ fixed}}\)) and variable costs (\(O_{W\text{ var}}\)) that scales with the annual energy production of the wind turbines (\(AEP_W\)) and the ratio between the reference turbine and selected turbine power rating. The wind turbine cost \(f_{WT}(D, P_{rated}, hh)\) trend depends on the rotor diameter, the WT rated power and the tower hub height and it is given by (Dykes et al., 2018). In order to have costs relative to a reference turbine, a user can provide

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the cost and the characteristics of the reference turbine \( f_{WTref}(D_{ref}, P_{ratedref}, h_{href}) \), from where the reference costs can be scaled, see equation 11.

\[
C_W = (f_{WT}/f_{WTref})(C_{WT} + C_{W_civil}) W_{MW}
\]

\[
O_W = W_{MW} O_{W fixed} + AEP_W (P_{ratedref}/P_{rated}) O_{W var}
\]

2.11 PV plant costs model

A simple PV plant cost model consists in estimating the total capital expenditure costs (CAPEX, \( C_S \)) and operational and maintenance costs (OPEX, \( O_S \)) as a function of the installed capacity \( S_{MW} \), solar AC to DC ratio \( r_{DC-AC} \). The user provides PV cost per MW (DC) installation costs \( C_{PV} + C_{Sinstall} \) and fixed operational costs \( O_{Sfx} \), while the inverter costs is provided per MW (AC) for a reference ratio of DC to AC \( (C_{invref}) \).

\[
C_S = (C_{PV} + C_{Sinstall}) S_{MW} r_{DC-AC} + C_{invref} (r_{DC-AC ref}/r_{DC-AC}) S_{MW}
\]

\[
O_S = O_{Sfx} S_{MW} r_{DC-AC}
\]

2.12 Battery costs model

The battery plant cost model consists in estimating the total capital expenditure costs (CAPEX, \( C_B \)) and operational and maintenance costs (OPEX, \( O_B \)) as a function of the number of batteries required during the plant lifetime \( N_b \), assuming replacement of batteries after degradation) given the new battery energy \( b_E \) and power capacities \( b_P \). The CAPEX model splits the energy capacity costs \( C_{bE} \) and power capacity dependent costs which include power capacity, installation and control system costs \( C_{bP} + C_{bBOP} + C_{bcontrol} \). An equivalent number of present batteries \( N_{Beq} \) is used to reflect the decrease in costs of battery though out the lifetime of the battery given a battery price reduction per year \( f_b \) and the time of replacement of the \( i_b \) battery in years \( y_b(i_b) \).

\[
C_B = N_{Beq} (C_{bE} b_E) + (C_{bP} + C_{bBOP} + C_{bcontrol}) b_P
\]

\[
O_B = O_{bE} b_E
\]

\[
N_{Beq} = \sum_{i_b=0}^{N_b-1} (1 - f_b) y_b(i_b)
\]

2.13 Electrical and shared infrastructure cost model (ele_cost)

A simple electrical infrastructure cost model consists in estimating the total capital expenditure costs (CAPEX, \( C_e \)) as a function of the grid capacity \( G_{MW} \), and balance of system costs and grid connection costs \( C_{BOS} + C_{grid} \) and land costs.

\[
C_e = (C_{BOS} + C_{grid}) G_{MW} + C_{land} A_{HPP}
\]

\[
O_e = 0
\]
2.14 HPP financial model

A simple financial model consists in considering a different weighted average cost of capital (WACC) for wind, PV and battery. The WACC after tax ($WACC_{after\ tax}$) then is the weighting sum of the WACCs for wind, PV, battery and electrical by their corresponding CAPEX, taking the mean WACC for the electrical costs shared across all technologies.

\[
C_H = C_W + C_S + C_b + C_{el} \\
O_H = O_W + O_S + O_b + O_{el} \\
WACC_m = (WACC_W + WACC_S + WACC_b)/3 \\
WACC_{tx} = (C_W WACC_W + C_S WACC_S + C_b WACC_b + C_{el} WACC_m)/C_H
\]

The financial model then estimates the yearly incomes ($I_y$) and cashflow ($F_y$) as function of the average revenue over the year ($R_y = \langle Pr(t) H(t) - l(t) \rangle_y$), the tax rate ($r_{tax}$) and $WACC_{tx}$. Net present value (NPV) and levelized costs of energy (LCoE) can then be calculated using the $WACC_{tx}$ as the discount rate, as well as the internal rate of return (IRR).

\[
I_y = (R_y - O_H)(1 - r_{tax})(1 - WACC_{tx}) \\
F_y = \begin{cases} 
-C_H & \text{for } y = 0 \\
I_y & \text{for } y > 0 
\end{cases} \\
NPV = \sum_y F_y/(1 + WACC_{tx})^y \\
0 = \sum_y F_y/(1 + IRR)^y \\
C_L = \sum_y (O_H/(1 + WACC_{tx})^y) + C_H \\
AEP_L = \sum_y (AEP_y/(1 + WACC_{tx})^y) \\
LCoE = C_L/AEP_L
\]

3 HPP sizing optimization

The HPP sizing optimization problem consists in minimizing LCoE or maximizing NPV over CAPEX by changing the design variables: rotor-tip to ground height clearance ($h_c$ in [m]), turbine’s specific power ($sp$ in [m²/MW]), turbine’s rated power ($p_{rated}$ in [MW]), number of wind turbines ($N_{wt}$), wind’s installation density ($\rho_W$, in [MW/km²]), solar capacity ($S_{MW}$), battery power capacity ($b_P$ in [MW]) and battery energy storage capacity in hours at battery power capacity ($b_{Eh}$). Furthermore, the sizing is forced to only take integer values of the design variables.
min \ y(x)

\[ y(x) = \begin{cases} 
- \frac{NPV}{C_H}(x) \\
LCoE(x) 
\end{cases} \]

\[ x = [h_c, sp, prated, N_{wt}, \rho_W, S_{MW}, \theta_{tlt}, \theta_{azim}, r_{DCAC}, B_P, B_{Eh}] \]

s.t. 
\[ D = 2\sqrt{\frac{P_{rated}}{(\pi sp)}} \]
\[ hh = h_c + D/2 \]
\[ W_{MW} = N_{wt} prated \]
\[ A_w = W_{MW}/\rho_W \]
\[ B_E = B_{Eh} B_P \]

4 Surrogate based optimization

Surrogate-based optimization is used as the outer sizing optimization in order to reduce the number of full model evaluations during a gradient-based optimization (Jones et al., 1998). In this work, we use the Gaussian process (or Kriging) implementation from the Surrogate Modeling Toolbox (SMT) (Bouhlel et al., 2019). Modern Kriging surrogates with partial least squares based training (KPLS) have been shown to be faster to train and evaluate because of the minimized number of meta-parameters obtained by applying dimensional reduction techniques such principal component analysis to the inputs (Bouhlel et al., 2016b). Furthermore, KPLS can be used to provide near optimal initial conditions in the training of standard Kriging (KPLSK) (Bouhlel et al., 2016a). KPLSK with squared exponential kernel and linear trend are used as a surrogate model over the design variables.

An updated version of the parallel efficient global optimization (Roux et al., 2020) is proposed in order to use a two-step approach to (a) explore (find regions with candidates for global optimal) and (b) refine (propose model simulations that help the convergence of EGO optimization on local optima). See Algorithm 1. An initial database of model simulations is generated using Latin hyper-cube sampling (LHS) (McKay et al., 2000; Jin et al., 2003). Then in each optimization iteration, an exploration step identifies regions with candidates for global optimal based on the evaluation of the expected improvement of the surrogate. This is done by parallel execution over \(10^4\) random samples (per parallel process) in the design space. Then the top-ranked \(EI_x\) points are clustered using Elkan’s K-mean clustering algorithm (Elkan, 2003) and the best performing point per cluster is selected as a candidate \((x_{EI}^+).\) A refinement step is performed around the current optimal perturbing of each dimension at a time \((x_{opt}^+),\) depending on the iteration convergence the refinement focuses on local perturbations or evaluations of extremes per input dimension. Finally the model is evaluated in parallel \((y^+ \leftarrow M(x^+)).\) The surrogate \(\hat{M}\) is then updated with the updated list of model evaluations \((x^+, y^+).\)
Algorithm 1 Parallel explore and refine EGO algorithm

\begin{align*}
    &x = \text{LHS}(n_0) \\
    &y = M(x) \\
    &x_{opt} = \arg\min_x (y) \\
    \text{while} \ i_{iter} < n_{max\ iter} \text{ do} \\
    &\hat{M} \leftarrow \text{train}(x, y) \\
    &EI_x = \text{EI}(\hat{M}, x_{opt}, x_x) \\
    &x^{+}_{EI} \leftarrow \text{get\_candidates}(x_x, EI_x) \\
    &\text{if} \ \epsilon \leq \epsilon_{tol} \text{ then} \\
    &\quad x_{opt}^{+} \leftarrow \text{perturb\_around\_point}(x_{opt}) \\
    &\text{else if} \ \epsilon > \epsilon_{tol} \text{ then} \\
    &\quad x_{opt}^{+} \leftarrow \text{extremes\_around\_point}(x_{opt}) \\
    &\text{end if} \\
    &x_{opt}^{+} = [x^{+}_{EI}, x_{opt}^{+}] \\
    &y_{opt}^{+} = M(x_{opt}^{+}) \\
    &x, y \leftarrow [x, x^{+}], [y, y^{+}] \\
    &\epsilon = 1 - y_{opt}^{+}/\min(y) \\
    &x_{opt} = \arg\min_x (y) \\
    &y_{opt} = \min(y) \\
    \text{end while}
\end{align*}

Initial simulation DB

Train surrogate model

Explore the expected improvement

Get optimal candidates based on EI

Refine around current best

Refine on single variable extremes

Concatenate inputs for evaluation

Parallel model evaluation

Update model evaluations

Update epsilon

Update current optimal inputs

Update current optimal

5 Results

A summary of assumptions costs and general specifications of HPP are presented in table 1. Two different scenarios for battery costs are presented on the example sites.

The detailed results of the hybrid plant sizing optimization based on LCoE or on NPV/$C_H$ in three different locations in India are presented in tables 2 and 3, for the cheap battery and expensive battery scenarios correspondingly.

Table 2 shows that batteries are installed for NPV/$C_H$-based optimal sizing at the current costs of batteries (expensive batteries scenario), but the business case (IRR) for HPP with storage is marginal (0.08 or 0.07). In general, the optimizer tries to minimize the penalties by over-planting the generation or by introducing storage. On the good solar site, an HPP of Wind, PV and storage is obtained for the NPV/$C_H$-based design, while a single technology PV plant is obtained for the LCoE-based design. Note that the business case is negative for the LCoE-based design. On the good wind site a single wind plant with over-planting is selected for NPV/$C_H$-based design, while a single wind plant without over-planting is obtained for LCoE-based designs. The final size is a combination of reductions of land costs and wake losses, as it can be seen in the selection of larger spacing ($\rho_W$) for the LCoE-based design. It is interesting to see that both designs have very similar final LCoE values, which
Table 1. Assumptions for the HPP sizing optimization with two scenarios for battery costs.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Expensive Batteries</th>
<th>Cheap Batteries</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grid [MW]</td>
<td>300</td>
<td>300</td>
</tr>
<tr>
<td>year_start</td>
<td>1995</td>
<td>1995</td>
</tr>
<tr>
<td>year_end</td>
<td>2019</td>
<td>2019</td>
</tr>
<tr>
<td>N_life</td>
<td>25</td>
<td>25</td>
</tr>
<tr>
<td>weeks_per_season_per_year</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>expected grid utilization (GU) at peak hours</td>
<td>42.5%</td>
<td>42.5%</td>
</tr>
<tr>
<td>wind_turbine_cost [Euro/MW]</td>
<td>851 000</td>
<td>851 000</td>
</tr>
<tr>
<td>wind_civil_works_cost [Euro/MW]</td>
<td>117 000</td>
<td>117 000</td>
</tr>
<tr>
<td>land_cost [Euro/km²]</td>
<td>1.5</td>
<td>1.5</td>
</tr>
<tr>
<td>wind_fixed_onm_cost [Euro/MW/year]</td>
<td>12 800</td>
<td>12 800</td>
</tr>
<tr>
<td>d_ref [m]</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>hh_ref [m]</td>
<td>80</td>
<td>80</td>
</tr>
<tr>
<td>tracking</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>solar_PV_cost [Euro/MW]</td>
<td>219 000</td>
<td>219 000</td>
</tr>
<tr>
<td>solar_hardware_installation_cost [Euro/MW]</td>
<td>242 000</td>
<td>242 000</td>
</tr>
<tr>
<td>solar_fixed_onm_cost [Euro/MW]</td>
<td>8 150</td>
<td>8 150</td>
</tr>
<tr>
<td>pv_deg_per_year</td>
<td>0.005</td>
<td>0.005</td>
</tr>
<tr>
<td>battery_energy_cost [Euro/MWh]</td>
<td>180 000</td>
<td>90 000</td>
</tr>
<tr>
<td>battery_power_cost [Euro/MW]</td>
<td>64 000</td>
<td>32 000</td>
</tr>
<tr>
<td>battery_BOP_installation_commissioning_cost [Euro/MW]</td>
<td>73 000</td>
<td>36 000</td>
</tr>
<tr>
<td>battery_control_system_cost [Euro/MW]</td>
<td>18 000</td>
<td>9 000</td>
</tr>
<tr>
<td>battery_energy_onm_cost [Euro/MWh/year]</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>battery_lifetime [Full load cycles]</td>
<td>8 000</td>
<td>8 000</td>
</tr>
<tr>
<td>battery_depth_of_discharge</td>
<td>90%</td>
<td>90%</td>
</tr>
<tr>
<td>battery_min_E</td>
<td>70%</td>
<td>70%</td>
</tr>
<tr>
<td>battery_charge_efficiency</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>battery_price_reduction_per_year</td>
<td>0.05</td>
<td>0.05</td>
</tr>
<tr>
<td>hpp_BOS_soft_cost [Euro/MW]</td>
<td>120 000</td>
<td>120 000</td>
</tr>
<tr>
<td>hpp_grid_connection_cost [Euro/MW]</td>
<td>37 100</td>
<td>37 100</td>
</tr>
<tr>
<td>wind_WACC</td>
<td>0.052</td>
<td>0.052</td>
</tr>
<tr>
<td>solar_WACC</td>
<td>0.048</td>
<td>0.048</td>
</tr>
<tr>
<td>battery_WACC</td>
<td>0.08</td>
<td>0.08</td>
</tr>
<tr>
<td>discount_factor</td>
<td>0.06</td>
<td>0.06</td>
</tr>
<tr>
<td>tax_rate</td>
<td>0.22</td>
<td>0.22</td>
</tr>
</tbody>
</table>
highlights the fact that you can meet an LCoE target with multiple combinations of technologies. On the bad solar and bad wind site, a hybrid wind, PV and storage plant is selected for the NPV/C_H-based design with a marginally positive business case. This illustrates why it is not possible to size HPP sites based on IRR, there are several configurations that will produce negative business cases and therefore have undefined IRR. Note that PV-only plants are in general over-planted (320 MW over 300 MW grid), the reason for this is to obtain a better annual energy production (AEP) and grid utilization factor (GUF).

Table 3 shows that hybrid plants only occur on NPV/C_H-based sizing optimization. This is in general an expected result from HPP sizing based on LCoE, as the optimizer will only select to install the technology that will provide the lowest LCoE. NPV/C_H-based HPP designs include batteries in all locations in order to minimize the penalties except in the good wind site where it can meet the expected peak generation (and avoid penalty) just by over-planting the wind plant. In general, the lower costs of batteries produce better business cases on the NPV/C_H-based sites, in particular in the bad solar and bad wind. An example period of operation of the NPV/C_H-based sites is shown in figure 8.

![Graph](https://doi.org/10.5194/wes-2023-83)

**Figure 8.** Example of 10 days operation for NPV optimized HPPs (top) good solar site (bottom) good wind site. Cheap battery scenario.
Table 2. HPP Sizing optimization results in the example sites with respect NPV/CH and LCoE for expensive batteries scenario.
### Table 3.

HPP Sizing optimization results in the example sites with respect NPV/\( C_H \) and LCoE for cheap batteries scenario.

<table>
<thead>
<tr>
<th>Site Design objective</th>
<th>Good solar LCoE</th>
<th>Good solar NPV/( C_H )</th>
<th>Good wind LCoE</th>
<th>Good wind NPV/( C_H )</th>
<th>Bad solar &amp; wind LCoE</th>
<th>Bad solar &amp; wind NPV/( C_H )</th>
</tr>
</thead>
<tbody>
<tr>
<td>longitude</td>
<td>68.54</td>
<td>77.50</td>
<td>8.33</td>
<td>77.92</td>
<td>77.92</td>
<td>17.29</td>
</tr>
<tr>
<td>latitude</td>
<td>23.54</td>
<td>679.80</td>
<td>24.00</td>
<td>679.80</td>
<td>627.42</td>
<td>627.42</td>
</tr>
<tr>
<td>altitude</td>
<td>29.88</td>
<td>29.88</td>
<td>200.0</td>
<td>200.0</td>
<td>10.0</td>
<td>10.0</td>
</tr>
<tr>
<td>( h_c ) [m]</td>
<td>10.0</td>
<td>10.0</td>
<td>10.0</td>
<td>10.0</td>
<td>23.9</td>
<td>24.7</td>
</tr>
<tr>
<td>( sp ) [m2/W]</td>
<td>200.0</td>
<td>4.0</td>
<td>74.0</td>
<td>4.0</td>
<td>23.9</td>
<td>24.7</td>
</tr>
<tr>
<td>( P_{rated} ) [MW]</td>
<td>1.0</td>
<td>1.0</td>
<td>74.0</td>
<td>1.0</td>
<td>23.9</td>
<td>24.7</td>
</tr>
<tr>
<td>( N_{wt} )</td>
<td>0.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>23.9</td>
<td>24.7</td>
</tr>
<tr>
<td>( \rho_W ) [MW/km(^2)]</td>
<td>5.8</td>
<td>9.0</td>
<td>9.0</td>
<td>9.0</td>
<td>9.0</td>
<td>6.0</td>
</tr>
<tr>
<td>( S_{MW} )</td>
<td>335.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>9.0</td>
<td>6.0</td>
</tr>
<tr>
<td>( \theta_{tilt} ) [deg]</td>
<td>28.9</td>
<td>35.2</td>
<td>0.0</td>
<td>0.0</td>
<td>9.0</td>
<td>6.0</td>
</tr>
<tr>
<td>( \theta_{azim} ) [deg]</td>
<td>210.0</td>
<td>210.0</td>
<td>175.8</td>
<td>187.8</td>
<td>210.0</td>
<td>210.0</td>
</tr>
<tr>
<td>( r_{DC-AC} )</td>
<td>1.5</td>
<td>1.7</td>
<td>1.2</td>
<td>1.2</td>
<td>1.6</td>
<td>2.0</td>
</tr>
<tr>
<td>( B_{P} ) [MW]</td>
<td>0.0</td>
<td>100.0</td>
<td>0.0</td>
<td>0.0</td>
<td>100.0</td>
<td>100.0</td>
</tr>
<tr>
<td>( B_{Eh} ) [h]</td>
<td>9.0</td>
<td>4.0</td>
<td>9.0</td>
<td>9.0</td>
<td>9.0</td>
<td>6.0</td>
</tr>
<tr>
<td>( C_{h_f} )</td>
<td>10.9</td>
<td>0.0</td>
<td>1.6</td>
<td>1.6</td>
<td>10.9</td>
<td>0.0</td>
</tr>
<tr>
<td>Grid [MW]</td>
<td>300</td>
<td>300</td>
<td>300</td>
<td>300</td>
<td>300</td>
<td>300</td>
</tr>
<tr>
<td>Wind [MW]</td>
<td>0</td>
<td>41</td>
<td>296</td>
<td>296</td>
<td>0</td>
<td>26</td>
</tr>
<tr>
<td>Solar [MW]</td>
<td>335</td>
<td>400</td>
<td>0</td>
<td>0</td>
<td>335</td>
<td>400</td>
</tr>
<tr>
<td>Battery Power [MW]</td>
<td>0</td>
<td>100</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>Battery Energy [MWh]</td>
<td>0</td>
<td>400</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>600</td>
</tr>
<tr>
<td>Number_of_batteries</td>
<td>0</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>Rotor diam [m]</td>
<td>80</td>
<td>80</td>
<td>119</td>
<td>119</td>
<td>60</td>
<td>80</td>
</tr>
<tr>
<td>Hub height [m]</td>
<td>50</td>
<td>50</td>
<td>69</td>
<td>69</td>
<td>43</td>
<td>50</td>
</tr>
<tr>
<td>NPV/( C_H )</td>
<td>-0.23</td>
<td>0.48</td>
<td>1.52</td>
<td>1.52</td>
<td>-0.64</td>
<td>0.31</td>
</tr>
<tr>
<td>NPV [MEuro]</td>
<td>-37.51</td>
<td>137.30</td>
<td>414.05</td>
<td>415.66</td>
<td>-102.14</td>
<td>95.96</td>
</tr>
<tr>
<td>IRR</td>
<td>0.00</td>
<td>0.10</td>
<td>0.18</td>
<td>0.18</td>
<td>0.00</td>
<td>0.09</td>
</tr>
<tr>
<td>CAPEX [MEuro]</td>
<td>161.8</td>
<td>284.1</td>
<td>272.5</td>
<td>273.5</td>
<td>168.5</td>
<td>310.7</td>
</tr>
<tr>
<td>OPEX [MEuro]</td>
<td>2.3</td>
<td>4.6</td>
<td>6.7</td>
<td>6.7</td>
<td>4.5</td>
<td>4.5</td>
</tr>
<tr>
<td>Wind CAPEX [MEuro]</td>
<td>0.0</td>
<td>43.0</td>
<td>215.6</td>
<td>215.6</td>
<td>0.0</td>
<td>27.3</td>
</tr>
<tr>
<td>Wind OPEX [MEuro]</td>
<td>0.0</td>
<td>1.5</td>
<td>6.7</td>
<td>6.7</td>
<td>0.0</td>
<td>0.9</td>
</tr>
<tr>
<td>PV CAPEX [MEuro]</td>
<td>113.5</td>
<td>147.8</td>
<td>0.0</td>
<td>0.0</td>
<td>120.2</td>
<td>173.0</td>
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<tr>
<td>PV OPEX [MEuro]</td>
<td>2.3</td>
<td>3.0</td>
<td>0.0</td>
<td>0.0</td>
<td>2.5</td>
<td>3.6</td>
</tr>
<tr>
<td>Batt CAPEX [MEuro]</td>
<td>0.0</td>
<td>43.7</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>61.7</td>
</tr>
<tr>
<td>Batt OPEX [MEuro]</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Shared CAPEX [MEuro]</td>
<td>48.3</td>
<td>49.6</td>
<td>57.0</td>
<td>57.9</td>
<td>48.3</td>
<td>48.7</td>
</tr>
<tr>
<td>Shared OpeX [MEuro]</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>penalty lifetime [MEuro]</td>
<td>379.4</td>
<td>58.3</td>
<td>71.0</td>
<td>69.9</td>
<td>437.6</td>
<td>42.3</td>
</tr>
<tr>
<td>AEP [GWh]</td>
<td>754.2</td>
<td>1061.1</td>
<td>1759.0</td>
<td>1764.3</td>
<td>700.9</td>
<td>1029.2</td>
</tr>
<tr>
<td>GUF</td>
<td>0.29</td>
<td>0.40</td>
<td>0.67</td>
<td>0.67</td>
<td>0.27</td>
<td>0.39</td>
</tr>
<tr>
<td>Total curtailment [GWh]</td>
<td>297</td>
<td>1375</td>
<td>0</td>
<td>0</td>
<td>233</td>
<td>376</td>
</tr>
<tr>
<td>opt time [min]</td>
<td>12</td>
<td>15</td>
<td>7</td>
<td>9</td>
<td>8</td>
<td>15</td>
</tr>
</tbody>
</table>

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6 Conclusions

NPV-over-CAPEX optimal hybrid power plants are obtained across India in order to mitigate the penalties of not reaching the expected energy generation at peak hours. Li-ion batteries are installed on sites that can not mitigate penalties by over-planting. The results show how changing from LCoE to NPV/$C_H$-based design allows the optimizer to over-plant the HPP to maximize the revenue by balancing the CAPEX, OPEX and power curtailment coming from the oversized design.

Battery degradation plays an important role in HPP sizing as the additional costs of replacing the battery two over three times will change the financial viability of the project. For this reason, future work will look into integrating constraints of the amount of battery load cycles or battery lifetime consumption within the EMS optimization.

Code and data availability. HyDesign is an open source code for design and control of utility scale wind-solar-storage based hybrid power plant (HPP). The documentation and example interactive examples are available at(https://topfarm.pages.windenergy.dtu.dk/hydesign/); the input data including weather and price signals for the example Indian sites used in this article are available in the HyDesign repository under examples (https://gitlab.windenergy.dtu.dk/TOPFARM/hydesign).

Author contributions. JPM is responsible for the model development, overall implementation and the article. HH implemented the rule-based correction method. MFM contributed to the implementation of the parallel EGO algorithm. MG contributed in the improvement of the EMS formulation. RZ contributed with the initial implementation of battery degradation model. KD provided funding and supervision. All authors contributed to the article.

Competing interests. The authors declare that there are no competing interests.

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References


