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Balancing wind-power fluctuation via onsite storage under uncertainty: Power-to-hydrogen-to-power versus lithium battery

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ABSTRACT

Imbalance costs caused by forecasting errors are considerable for grid-connected wind farms. In order to reduce such costs, two onsite storage technologies, i.e., power-to-hydrogen-to-power and lithium battery, are investigated considering 14 uncertain technological and economic parameters. Probability density distributions of wind forecasting errors and power level are first considered to quantify the imbalance and excess wind power. Then, robust optimal sizing of the onsite storage is performed under uncertainty to maximize wind-farm profit (the net present value). Global sensitivity analysis is further carried out for parameters prioritization to highlight the key influential parameters. The results show that the profit of power-to-hydrogen-to-power case is sensitive to the hydrogen price, wind forecasting accuracy and hydrogen storage price. When hydrogen price ranges in (2, 6) €/kg, installing only electrolyzer can earn profits over 100 k€/MW_{WP} in 9% scenarios with capacity below 250 kW/MW_{WP}, under high hydrogen price (over 4 €/kg); while installing only fuel cell can achieve such high profits only in 1.3% scenarios with capacity below 180 kW/MW_{WP}. Installing both electrolyzer and fuel cell (only suggested in 22% scenarios) results in profits below 160 k€/MW_{WP}, and particularly 20% scenarios allow for a profit below 50 k€/MW_{WP} due to the contradictory effects of wind forecasting error, hydrogen and electricity price. For lithium battery, investment cost is the single highly influential factor, which should be reduced to 760 €/kWh. The battery capacity is limited to 88 kW h/MW_{WP}. For profits over 100 k€/MW_{WP} (in 3% scenarios), the battery should be with an investment cost below 510 €/kWh and a depth of discharge over 63%. The power-to-hydrogen-to-power case is more advantageous in terms of profitability, reliability and utilization factor (full-load operating hours), while lithium battery is more helpful to reduce the lost wind and has less environmental impact considering current hydrogen market.

1. Introduction

Power generation from renewable energy has been widely considered as a promising means to minimize the environmental impacts of power generation [1]. Under restrict CO_2 emission regulation, renewable energy is expected to contribute 57–71% of the global electricity with the highest increase from wind power [2].

Wind farms usually participate in the energy market, e.g., the day-ahead spot market. For day-ahead energy bidding, the generation of wind power in each time interval should be forecasted. However, the wind forecasting (WF) has inevitable errors, leading to imbalance costs sustained by Transmission System Operator (TSO). The payments to TSOs are quantified by the imbalance energy prices and amount. In Denmark, the payment corresponds to 3–15% of the wholesale electricity prices in 2017 [3], causing considerable reduction of profits of wind farms. Except for using balancing service of TSOs, onsite energy storage system (ESS), installed directly in the wind farms as balancing reserve, is a promising alternative to reduce the imbalance costs by storing excess or unexpected wind power generated and releasing it when needed [4–8].

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ESSs have been and are currently developed intensively to cope with high penetration of non-renewable-dispatchable renewables [8]. However, considering that the pumped-hydro storage and compressed air energy storage are restricted to geographical locations [9], and thermal storage suffers from high exergy-destruction and losses [10], only few ESSs are technically suitable for onsite wind-power storage, for example, battery and power-to-hydrogen-to-power (PHP) via electrolyzer (EL) and fuel cell (FC) [4,8].

PHP can convert excess renewable electricity into gas (particularly, hydrogen in line with hydrogen economy [11]) by the EL system, store or trade the hydrogen produced, and convert the stored or imported hydrogen back to electricity by the FC system [12–14]. The hydrogen generated can also be injected to existing natural-gas grid up to 20 vol% to avoid expensive hydrogen storage [15]. The PHP systems can be employed in wind farms for large-scale seasonal storage, spinning reserve, peak shaving, oscillation damping [16] and load following. There has been one wind-power driven PHP system demonstrated in Utsira (Norway) [17]: wind power (600 kW)–alkaline (ALK) EL (10 Nm^3/h)–polymer electrolyte membrane (PEM) FC (10 kW)–hydrogen storage (2400 Nm^3, 200 bar). This system has been operated continuously since 2004 with 90% availability and good power quality. However, the demonstration plant was operated in a stand-alone mode without participating the energy market. For grid connection, the major obstacle is the high cost of hydrogen storage due to time-decoupled hydrogen production and consumption [18]. The PHP system can significantly reduce the impacts of forecasting errors, for example, up to 17% for a 100 MW wind farm with relatively small capacities of FC (0.2 MW) and EL (0.7 MW); however, the hydrogen price needs to be below 1.25 €/kg (not considering hydrogen storage) to be profitable [11]. To further enhance its economic viability, the incentives for green gas and technology advances (e.g., efficiency improvement and lifespan increase) are also beneficial [19,20].

Lithium battery (LB) is advantageous with high energy density, fast charging/discharging capability [21]. Thus, it can be employed to provide (1) ancillary service as primary reserve (second scale) [22], and secondary and tertiary control reserve (minute scale), (2) behind-the-meter frequency regulation [23], and (3) long-timescale energy management. The LB is also potential for balancing wind forecasting errors (WFEs) but it suffers from high investment cost [4] and limited charge-discharge cycles [21]. It has been predicted that the LB is capable of increasing wind-farm revenue by 29% in 2050 with the battery price reduced down to 333 €/kWh [24], but the revenue can be decreased considerably considering battery replacement costs and variable market prices. The investment cost should be decreased further down to 105 €/kWh using 400 kW h/MW_{WP} battery and the performances to be economically viable [25]. The feasibility of LB for wind-farm applications tends to be higher under high forecasting errors [26].

Many uncertain parameters have important influence on the economic viability of reducing the impacts of WFEs via onsite PHP and LB, e.g., market prices (electricity, imbalance, hydrogen trade, hydrogen storage), incentives, investment costs, storage lifespans, storage efficiencies, wind forecasting accuracy. The literature investigation the onsite ESSs are listed and compared in Table A 1, highlighting the following drawbacks:

- Only limited uncertain parameters or even only extreme scenarios were investigated. The uncertainties identified in literature have never been considered simultaneously in one single investigation.
- The literature usually adopted local sensitivity analysis (LSA) to evaluate the uncertainty, i.e., evaluating one parameter while fixing all remaining parameters [4,17,19,21,24], or evaluating only a few combinations of uncertain parameters [11,20,23]. The LSA fails to evaluate the interaction among different uncertain parameters and the trends of objective when these parameters vary simultaneously.

Correspondingly, in this paper, the feasibility of onsite PHP and LB to increase wind-farm profitability is investigated by a robust optimal sizing method considering a complete set of 14 uncertain parameters. Furthermore, global sensitivity analysis is adopted to quantify the effect of varying uncertain parameters simultaneously and rank the factor prioritization, so that the scenarios with higher profitability can be identified.

The paper was organized as follows: in section 2, the detail operational criteria of grid-connected wind-storage system were introduced. Then, the sizing optimization under uncertainty was proposed and the global sensitivity analysis (GSA) was carried out to analyze the effect of each uncertain parameter (section 3). Finally, a case was studied to verify the model and the analysis in section 4. The investigation was concluded in section 5.

2. Operation of grid-connected wind farms

Electricity generated by wind farms can be exchanged in a pool, in which wind farm operators should submit hourly energy bids to the day-ahead market based on their power production forecasted. After bidding, a schedule including the dispatched power profiles to be followed by the wind farms is released. However, due to the imperfect forecast, there are inevitable deviations between the dispatched power and actual power of the wind farms, which leads to frequency deviation of the electrical grid. The resulting imbalance should be managed by the TSO, and the cost of the balancing service is undertaken as the imbalance costs paid by wind farm operators [27].

By storing excess wind power and releasing it when needed, onsite ESSs can reduce the difference between forecasting power and scheduled power accepted by the day-ahead market, and thus reduce the imbalance costs. In Fig. 1 (a), positive deviations (when actual power is higher than the dispatched power) are handled by the EL or the charge of batteries; while negative deviations are handled by the FC or the discharge of batteries. For the applications of FC and EL, the hydrogen produced and stored can be interacted with the market.

The interaction of wind farms and the electrical grid in one day is illustrated in Fig. 1 (b), which also shows how the onsite ESSs can help reduce the imbalance. Wind farms tend to declare to electrical grid a dispatched WP lower than the forecasting WP, to avoid large imbalance penalty. Within 0–7 and 15–23 h when the actual wind power is higher than the forecasting, the excess wind power will be curtailed without onsite ESSs; otherwise, all or part of the excess power (blue area) can be stored depending on the state of charge of the ESSs and those cannot be stored will be lost eventually (green area). Within 7–11 h when the dispatched power is higher than the actual power, the difference can be completely or partially compensated by the discharge of the ESSs (yellow area), thus reducing the imbalance (red area) exposed to the electrical grid. The service provided by the onsite ESSs depends on the size of installed ESSs, which in turn affects the economic feasibility.

3. Methodology of robust optimal storage sizing under uncertainty

There exists an optimal size of onsite ESSs to maximize the profit of wind farms: an increased storage size allows to reduce more power imbalance and related costs, while the investment costs will be increased in turn.

3.1. Profitability of onsite ESSs

The benefit of such onsite ESSs are compared with a base case where no ESS is installed in wind farms. The net present value (*NPV*) for the benefit assessment does not consider the investment and O&M costs of the wind farms since these costs are regarded as the same no matter whether ESSs are employed or not.

The *NPV* for optimal storage sizing Eq. (1) considers, as shown in

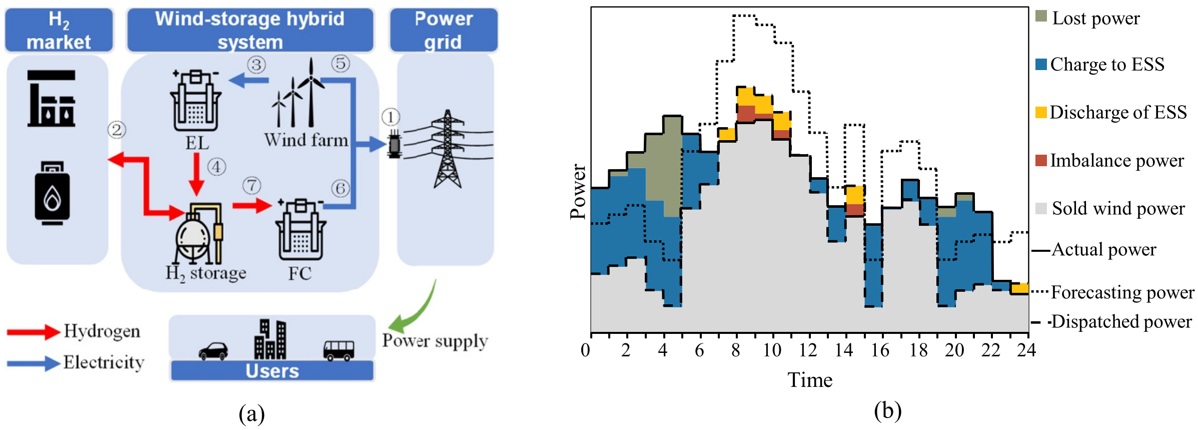

Fig. 1. The scheme of wind farm operation with onsite ESSs.

Fig. 1 (a), the increased revenue from electricity sale (ΔC_j^{ele}, ①) and the reduced imbalance costs (ΔC_j^{imb}) compared with base case, the additional revenue (positive) or cost (negative) of hydrogen trade with the gas market (ΔC_j^{hyd}, ②), the incentive allowance of hydrogen (C_j^{HI}), the costs of hydrogen storage (C_j^{HS}), as well as the initial investment ($C_0^{inv,ESS}$), the replacement costs ($C_j^{inv,ESS,rep}$) and O&M costs ($C_j^{O\&M,ESS}$) of the ESSs:

$$NPV = \sum_{j=1}^{\tau} \frac{\Delta C_j^{ele} + \Delta C_j^{imb} + \Delta C_j^{hyd} + C_j^{HI} - C_j^{HS} - C_j^{inv,ESS,rep} - C_j^{O\&M,ESS}}{(1+i)^j} - C_0^{inv,ESS} \tag{1}$$

where τ is the lifespan of wind farms, which is set typically as 20 years; i is the discount rate (5%). The increased revenue of electricity sale (€/year) can be calculated as:

$$\Delta C_j^{ele} = \left(\Delta W_j^{wind} + W_j^{dis,ESS}\right)\left(\tilde{\theta}_{ele} + \tilde{\theta}_{sub}\right) \tag{2}$$

where ΔW_j^{wind} is the increased wind electricity sold to the grid (⑤ in Fig. 1), MWh/year; $W_j^{dis,ESS}$ is the electricity from the discharge of the storage (⑥ in Fig. 1), MWh/year; $\tilde{\theta}_{ele}$ is the market price of electricity, €/MWh; $\tilde{\theta}_{sub}$ is the government subsidy for environmentally-friendly wind power, €/MWh.

For the PHP cases, there is a revenue or cost of hydrogen trade (ΔC_j^{hyd}, ② in Fig. 1):

$$\Delta C_j^{hyd} = \left(3600 * \frac{\tilde{\theta}_{\eta_{EL}} W_j^{cha,ESS}}{LHV} - \frac{3600 * W_j^{dis,ESS}}{\tilde{\theta}_{\eta_{FC}} * LHV}\right)\tilde{\theta}_{hyd} \tag{3}$$

where ΔC_j^{hyd} is decided by the net produced hydrogen, i.e., the hydrogen produced by EL (④ in Fig. 1) subtracting the part consumed by FC (⑦ in Fig. 1); $\tilde{\theta}_{hyd}$ is the market price of hydrogen, €/kg; $W_j^{cha,ESS}$ is the excess power sent to and consumed by the electrolysis (③ in Fig. 1), MWh/year; $\tilde{\theta}_{\eta_{EL}}$ is the efficiency of EL system, -; $W_j^{dis,ESS}$ is the electricity generated by FC (⑥ in Fig. 1), MWh/year; $\tilde{\theta}_{\eta_{FC}}$ is the efficiency of FC system, -; LHV is the lower heating value of hydrogen, MJ/kg.

The reduced imbalance cost ΔC_j^{imb} due to the installed storage systems can be calculated by the decreased imbalance electricity ΔW_j^{imb}(MWh) and the imbalance price ($\tilde{\theta}_{imb}$, €/MWh):

$$\Delta C_j^{imb} = \Delta W_j^{imb}\tilde{\theta}_{imb} \tag{4}$$

In the above formulations, the electricity charge to ESSs ($W_j^{cha,ESS}$) and discharge from ESSs ($W_j^{dis,ESS}$), the wind electricity sold to the grid (W_j^{wind}) and the imbalanced electricity (W_j^{imb}) can be calculated based on Fig. 1, according to Fig. 2.

The possible incentive to green hydrogen C_j^{HI} [11] is expressed with the incentive price ($\tilde{\theta}_{HI}$, €/MWh) as:

$$C_j^{HI} = W_j^{cha,ESS}\tilde{\theta}_{HI} \tag{5}$$

For hydrogen storage costs C_j^{HS}, the hydrogen storage price ($\tilde{\theta}_{HS}$, €/kg) is represented by the levelized cost of hydrogen storage [28]:

$$C_j^{HS} = 3600 * \frac{\tilde{\theta}_{\eta_{EL}} W_j^{cha,ESS}}{LHV}\tilde{\theta}_{HS} \tag{6}$$

The initial investment cost $C_0^{inv,ESS}$ of PHP is considered as:

$$C_0^{inv,ESS} = cap_0^{FC}\tilde{\theta}_{inv,FC} + cap_0^{EL}\tilde{\theta}_{inv,EL} \tag{7}$$

where cap_0^{FC} and cap_0^{EL} are the installed capacities of the FC and EL, MW. $\tilde{\theta}_{inv,\ FC}$ and $\tilde{\theta}_{inv,EL}$ are the prices of FC and EL, respectively, €/MW.

The initial investment cost of the LB is calculated as:

$$C_0^{inv,ESS} = cap_0^{LB}\tilde{\theta}_{inv,LB} \tag{8}$$

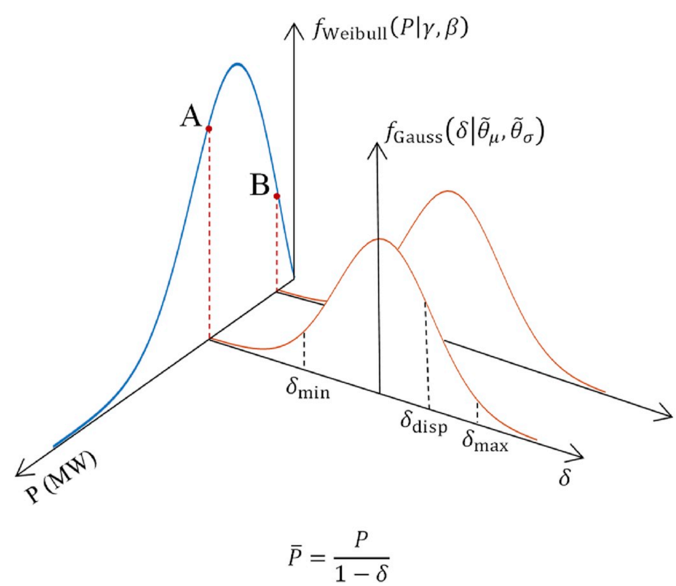

Fig. 2. The factors affecting wind-farm profits.

where cap_0^{LB} is the installed capacity of LB, kWh, and $\tilde{\theta}_{\mathrm{inv,LB}}$ is the capital cost, €/kWh.

The replacement costs are considered as:

$$C_j^{\mathrm{inv,ESS,rep}} = C_0^{\mathrm{inv,ESS}} rep_j \tag{9}$$

where rep_j is 1 when there is a replacement of the ESS in year j; otherwise, rep_j is 0. In this study, the capacity of each replacement is the same as the installed capacity (cap_0^{FC}, cap_0^{EL} or cap_0^{LB}). Defining the end of life of the PEM fuel cell and ALK electrolysis remains a question [29], so the lifespans of FC and EL are not estimated and simplified as certain years ranging in uncertain ranges ($\tilde{\theta}_{\mathrm{life,FC}}$, $\tilde{\theta}_{\mathrm{life,EL}}$). The replacement of LB might be caused by repeated deep cycles resulting in a gradual reduction $Loss_{\mathrm{LB}}$(%/cycle), while the allowable depth of discharge (DOD) of repeated cycles is uncertain in different operational models ($\tilde{\theta}_{\mathrm{DOD}}$). A battery will end its life until the useable capacity is below a predetermined percentage, which is normally set as 80% [30]. Thus, the uncertain lifespan of LB $\tilde{\theta}_{\mathrm{life,LB}}$ is decided by the uncertain parameter $\tilde{\theta}_{\mathrm{DOD}}$ [31]:

$$1 - \tilde{\theta}_{\mathrm{life,LB}} Loss_{\mathrm{LB}} \frac{\eta_{\mathrm{LB}} W_j^{\mathrm{dis,ESS}}}{\tilde{\theta}_{\mathrm{DOD}} cap_0^{\mathrm{LB}}} = 80\% \tag{10}$$

$$Loss_{\mathrm{LB}} = \frac{20}{33000\ e^{-0.06576\ \tilde{\theta}_{\mathrm{DOD}}+3277}} \tag{11}$$

Thus, the replacements of FC, EL and LB are calculated:

$$rep_j = \begin{cases} 1 & \mathrm{integral}\left(\tilde{\theta}_{\mathrm{life}}+1, 2\tilde{\theta}_{\mathrm{life}}+1, 3\tilde{\theta}_{\mathrm{life}}+1, \ldots\right) \\ 0 & \mathrm{others} \end{cases} \quad j \in \left[1, \tau\right] \tag{12}$$

where η_{LB} is the efficiency of LB and is set as 95%.

The O&M costs $C_j^{\mathrm{O\&M,ESS}}$ are assumed to be proportional to the installed capacity. The O&M costs are set as 4% and 1% of investment cost for the FC-EL ESS [13] and LB, respectively. Except this, using FC, the O&M costs should also add the hydrogen purchase.

3.2. Wind power generation and forecasting error

Wind power generation and forecasting errors can be estimated by the statistical distributions from sufficient historical data. The two-parameter Weibull distribution, as illustrated in Fig. 2 (blue line), is recognized as appropriate for representing wind-power generation [32]:

$$f_{\mathrm{Weibull}}(P|\gamma,\beta) = \frac{\gamma}{\beta^{\gamma}} P^{(\gamma-1)} \mathrm{e}^{-\left(\frac{P}{\beta}\right)^{\gamma}} \quad (\gamma,\beta > 0) \tag{13}$$

where the P represents the forecasting wind power, MW; $f_{\mathrm{Weibull}}(P|\gamma,\beta)$ is the Weibull distribution probability density of P; γ and β are the shape and scale parameters, respectively. The area below the blue line in Fig. 2 represents the annual electricity production.

Wind forecasting error is typically modeled as a Gauss distribution [33] as illustrated in Fig. 2 (orange lines):

$$f_{\mathrm{Gauss}}\left(\delta|\tilde{\theta}_{\mu}, \tilde{\theta}_{\sigma}\right) = \frac{1}{\sqrt{2\pi}\tilde{\theta}_{\sigma} \mathrm{e}^{-\frac{(\delta-\tilde{\theta}_{\mu})^2}{2\tilde{\theta}_{\sigma}^2}}} \tag{14}$$

$$\delta = \frac{\Delta P}{P} = \frac{\overline{P} - P}{\overline{P}} \tag{15}$$

where δ is the relative error; $f_{\mathrm{Gauss}}(\delta|\tilde{\theta}_{\mu}, \tilde{\theta}_{\sigma})$ is the probability density of δ; $\tilde{\theta}_{\mu}$ is the expected value; $\tilde{\theta}_{\sigma}$ is the standard deviation; $\overline{P}$ is the actual wind power, MW.

As shown in Fig. 2, each power (e.g., A and B) in the power-generation distribution $f_{\mathrm{Weibull}}(P|\gamma,\beta)$ has an uncertain forecasting error following the distribution of $f_{\mathrm{Gauss}}(\delta|\tilde{\theta}_{\mu}, \tilde{\theta}_{\sigma})$. Wind farms should optimize the dispatched wind power P_{disp} considering the forecasting error δ_{disp}. Taking A as an example, for a given dispatched power P_{disp}, the actual power $\overline{P}$ has four scenarios:

- $\delta < \delta_{\mathrm{min}}$: $\overline{P}$ is much lower than P_{disp} and even beyond the discharge capacity of the onsite ESSs. There will be imbalance power and a penalty for the wind farm.
- $\delta_{\mathrm{min}} < \delta < \delta_{\mathrm{disp}}$: $\overline{P}$ is lower than P_{disp} and the imbalance power can be completely supplied by the onsite ESSs. There will be no penalty for wind farm.
- $\delta_{\mathrm{disp}} < \delta < \delta_{\mathrm{max}}$: $\overline{P}$ is higher than P_{disp} and the excess power can be stored by the ESSs. Wind farm generates the dispatched power without curtailing wind power.
- $\delta > \delta_{\mathrm{max}}$: $\overline{P}$ is much higher than P_{disp} and the excess power can only be used or stored partly. Wind farm generates the dispatched power with wind curtailment.

Therefore, the probability of generating dispatched power by wind farm, i.e. the reliability of the wind farm, can be evaluated by the following equation:

$$\Phi = \int_{\delta_{\mathrm{min}}}^{1} f_{\mathrm{Gauss}}\left(\delta|\tilde{\theta}_{\mu}, \tilde{\theta}_{\sigma}\right) d\delta \tag{16}$$

3.3. Robust optimal sizing of onsite ESSs under uncertainty

There are technical and economic uncertainties affecting the robustness of the evaluation for the benefits of the onsite ESSs. It is not credible to draw conclusions based on fixed technical and economic assumptions. The uncertain parameters affecting the profits of the onsite ESSs need to be considered, as listed in Table 1.

For PHP case, the optimization problem with uncertainty is formulated as:

$$max\ NPV = g_{\tilde{\boldsymbol{\theta}}}\left(\Phi, cap_0^{\mathrm{FC}}, cap_0^{\mathrm{EL}}\right), \tag{17}$$

$$\tilde{\boldsymbol{\theta}} = \left\{\tilde{\theta}_{\mathrm{ele}}, \tilde{\theta}_{\mathrm{sub}}, \tilde{\theta}_{\mathrm{hyd}}, \tilde{\theta}_{\eta_{\mathrm{EL}}}, \tilde{\theta}_{\eta_{\mathrm{FC}}}, \tilde{\theta}_{\mathrm{HI}}, \tilde{\theta}_{\mathrm{imb}}, \tilde{\theta}_{\mathrm{HS}}, \tilde{\theta}_{\mathrm{inv,FC}}, \tilde{\theta}_{\mathrm{inv,EL}}, \tilde{\theta}_{\mu}, \tilde{\theta}_{\sigma}, \tilde{\theta}_{\mathrm{life,FC}}, \tilde{\theta}_{\mathrm{life,EL}}\right\}$$

For LB case, the optimization problem is with less uncertain pa-

Table 1
Uncertain parameters considered.

Uncertain inputs	Description	Unit	Range	Literatures
$\tilde{\theta}_{\mathrm{ele}}$	Electricity price	€/MWh	[40,100]	[34]
$\tilde{\theta}_{\mathrm{sub}}$	Government subsidy	€/MWh	[13,60]	[35]
$\tilde{\theta}_{\mathrm{hyd}}$	Hydrogen price	€/kg	[2,6]	[36]
$\tilde{\theta}_{\eta_{\mathrm{EL}}}$	EL efficiency	–	[0.62,0.82]	[37]
$\tilde{\theta}_{\eta_{\mathrm{FC}}}$	FC efficiency	–	[0.5,0.6]	[38]
$\tilde{\theta}_{\mathrm{HI}}$	Hydrogen incentive	€/MWh	[0,20]	[18]
$\tilde{\theta}_{\mathrm{imb}}$	Imbalance price	€/MWh	[195,300]	[18]
$\tilde{\theta}_{\mathrm{HS}}$	Hydrogen storage price	€/kg	[1,3]	[27,39]
$\tilde{\theta}_{\mathrm{inv,FC}}$	FC investment cost	€/kW	[200,1500]	[40,41]
$\tilde{\theta}_{\mathrm{life,FC}}$	FC lifespan	Years	[2,7]	[42]
$\tilde{\theta}_{\mathrm{inv,EL}}$	EL investment cost	€/kW	[370,1100]	[36]
$\tilde{\theta}_{\mathrm{life,EL}}$	EL lifespan	Years	[7,12]	[36]
$\tilde{\theta}_{\mathrm{inv,LB}}$	LB investment cost	€/kWh	[238,1500]	[43]
$\tilde{\theta}_{\mathrm{DOD}}$	DOD allowable interval	–	[0.5,1]	[44,24]
$\tilde{\theta}_{\mu}$	Expected value of WFE	–	[-0.3,0.3]	
$\tilde{\theta}_{\sigma}$	Standard deviation of WFE	–	[0.01,0.1]	

rameters:

$$\max NPV = g_{\tilde{\theta}}\left(\Phi, cap_0^{\mathrm{LB}}\right) \tag{18}$$

$$\tilde{\boldsymbol{\theta}} = \left\{\tilde{\theta}_{\mathrm{ele}}, \tilde{\theta}_{\mathrm{sub}}, \tilde{\theta}_{\mathrm{imb}}, \tilde{\theta}_{\mathrm{inv,LB}}, \tilde{\theta}_{\mathrm{DOD}}, \tilde{\theta}_{\mu}, \tilde{\theta}_{\sigma}\right\}$$

The uncertain parameters need to be characterized first to determine the most influential ones, which can be achieved by local or global sensitivity analysis (LSA vs GSA) [45]. Uncertain parameters are changed in a one-at-a-time scheme in LSA but simultaneously in GSA, which thus considers the interaction among different parameters [46]. Several GSA methods are available in literature, among which a variance-based method is recommended [44]. The importance of an uncertain parameter is evaluated by the first-order sensitivity indices S_k [44]:

$$S_k = \frac{V[E(NPV|\tilde{\theta}_k)]}{V(NPV)} = \frac{g_A \cdot g_{C_k} - g_0^2}{g_A \cdot g_A - g_0^2} \tag{19}$$

where E is expected value; V is variance; $g_0^2 = \left(\frac{1}{N}\sum_{n=1}^{N} g_A^n\right)^2$.

The Monte-Carlo method [47] extended by Ref. [44] is employed to calculate the sensitivity indices S_k with the following steps:

- Generate two (N, m) matrixes $A\{x_k\}$ and $B\{x_k\}$ randomly. The set x_k are in the ranges of $\tilde{\theta}_k$ (Table 1). The N is the number of samples and can vary from a few hundreds to a few thousands. The m is the number of uncertain parameters, $k \in [1, m]$.
- Define a matrix $C_k\{x_k\}$ formed by all columns of $B\{x_k\}$ except the kth column, which is taken from $A\{x_k\}$.
- Compute the NPV for all the input samples in matrices A, B, and C_k, obtaining the vectors of NPV of dimension $N \times 1$: g_A g_B g_{C_k}, which are all needed to calculate the sensitivity indices S_k.

As illustrated in Fig. 3, the solving procedures of the robust optimal sizing starts with the fitting of historical wind power data as a fixed Weibull distribution f_{Weibull} (Eq. (13)). Considering the selected uncertain parameters $\tilde{\boldsymbol{\theta}}$, a set of scenarios are generated by the sampling method employed. For each scenario, the WFE distribution f_{Gauss} (Eq. (14)) is assumed by the sampled parameters $\tilde{\theta}_{\mu}$ and $\tilde{\theta}_{\sigma}$, while the electricity of wind, imbalance, storage (W_j^{wind}, W_j^{imb}, $W_j^{\mathrm{cha,ESS}}$, $W_j^{\mathrm{dis,ESS}}$) are obtained based on the statistical distribution (Table A 2). Then, the optimal sizing cap_0^{FC}, cap_0^{EL}, $cap_0^{\mathrm{LB}}$are obtained by maximizing NPV(Eq. (1)).

4. Case study

The wind parks in four Northern European countries, i.e., Norway, Denmark, Sweden, and Finland, were chosen as the case study [48]. The historical hourly power-generation data from 01.01.2017 to 01.01.2018 were employed. The total installed capacity of wind power was 14, 123 MW. The distribution of power generation was fitted according to Eq. (13) with the obtained parameters: $\gamma = 2.14$, $\beta = 0.34$ and a root mean square error (RMSE) of 0.57%. The number of samples N is 200.

4.1. Economic assessment and sensitivity analysis

4.1.1. The power-to-hydrogen-to-power case

By solving the optimization problem described in section 3.3 under each scenario (i.e., a combination of values of uncertain parameters), the optimal reliability Φ, and the capacities of fuel cell (cap_0^{FC}) and electrolyzer (cap_0^{EL}) are obtained with a maximized NPV, as shown in Fig. 4 (a). The PHP can bring profits under 98.6% scenarios, represented by positive NPV. Considerable profits with an NPVeven up to 600 k€/MW$_{\mathrm{WP}}$ are possible under the scenario $\tilde{\boldsymbol{\theta}}$ = {43.7, 13.4, 6, 0.68, 0.57,

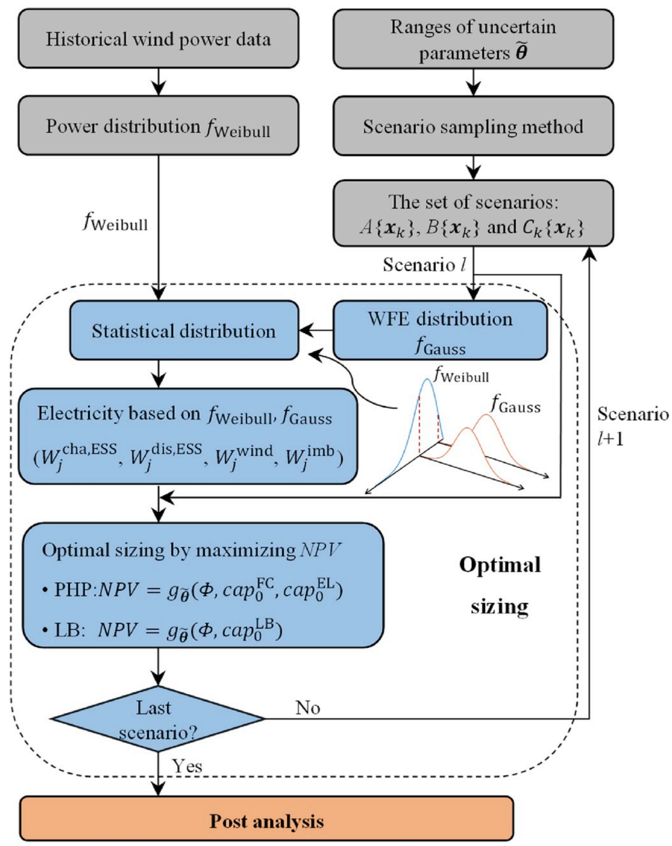

Fig. 3. Robust optimal sizing of onsite storage under uncertainty.

18.0, 227.0, 1.46, 601.8, 473.1, 0.17, 0.096, 2.7, 9.1} by installing 190 kW/MW$_{\mathrm{WP}}$ EL and no FC. The onsite PHP can also enhance the reliability of the wind farms, since the probability Φ of generating the dispatched power (0.62, 0.99) is always higher than that of the base cases (0.53, 0.85).

4.1.1.1. Overview of all scenarios and the key influential uncertain parameters. Hybrid systems having high NPVs tend to install either a large-capacity EL or a large-capacity FC as shown in Fig. 4 (b). Installing both EL and FC is suggested in only 22% scenarios with NPV below 161 k€/MW$_{\mathrm{WP}}$, and even 20% scenarios have profits less than 50 k€/MW$_{\mathrm{WP}}$. The optimal capacity are below 250 and 160 kW/MW$_{\mathrm{WP}}$ for EL and FC respectively, which represent 25% and 16% of the installed wind capacity. The EL is employed in 78% scenarios, while FC is only used in 43% scenarios. For 72% of all scenarios considered, the EL capacity is higher than the FC capacity, meaning that EL is more profitable than FC under most scenarios. Moreover, under 66% of all scenarios, the EL capacity is more than 3 times of the FC capacity.

The factor prioritization of uncertain parameters, ranked by s_k, are shown in Table 2. The most sensitive factor on revenue is the hydrogen price $\tilde{\theta}_{\mathrm{hyd}}$, followed by the forecasting quality, represented by $\tilde{\theta}_{\sigma}$ and $\tilde{\theta}_{\mu}$. The quality of wind forecasting directly reflects the magnitude of imbalance power and determines the storage size. Other important factors include hydrogen storage price $\tilde{\theta}_{\mathrm{HS}}$, investment cost of EL ($\tilde{\theta}_{\mathrm{inv,EL}}$), government subsidy $\tilde{\theta}_{\mathrm{sub}}$. Less influential parameters are FC efficiency ($\tilde{\theta}_{\eta_{\mathrm{FC}}}$), investment ($\tilde{\theta}_{\mathrm{inv,FC}}$), imbalance price $\tilde{\theta}_{\mathrm{imb}}$, EL lifespan ($\tilde{\theta}_{\mathrm{life,EL}}$), hydrogen incentive ($\tilde{\theta}_{\mathrm{HI}}$), FC lifespan ($\tilde{\theta}_{\mathrm{life,FC}}$), electricity price $\tilde{\theta}_{\mathrm{ele}}$ and EL efficiency $\tilde{\theta}_{\eta_{\mathrm{EL}}}$. These observations might prioritize the technological development of for such applications as (1) decreasing EL investment cost, (2) increasing FC efficiency, and (3) decreasing FC investment cost. Prolonging the lifespans are, unfortunately, not as

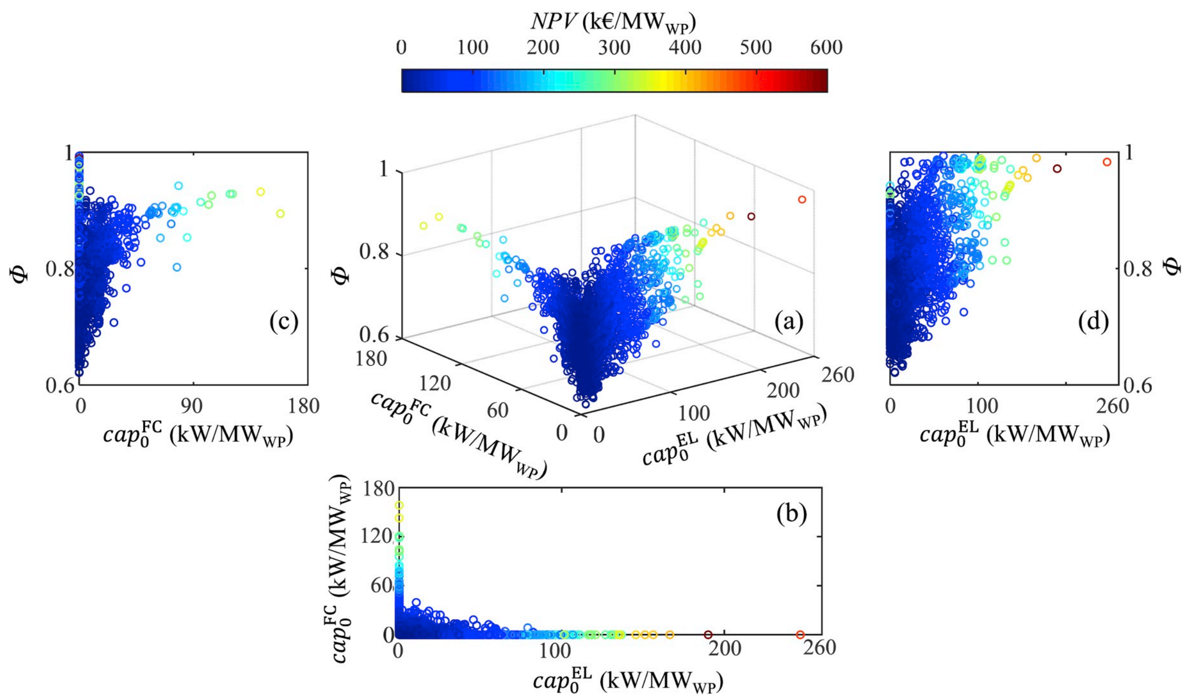

Fig. 4. The cap_0^{FC}, cap_0^{EL}, Φ corresponding to the maximized *NPV* under each scenario considered for the PHP case.

Table 2
Factor prioritizations of uncertain parameters for the PHP case.

Uncertain parameters	Description	Sensitivity index s_k	Rank
$\tilde{\theta}_{\mathrm{hyd}}$	Hydrogen price	0.2807	1
$\tilde{\theta}_{\sigma}$	Standard deviation of WFE	0.2014	2
$\tilde{\theta}_{\mu}$	Expected value of WFE	0.1382	3
$\tilde{\theta}_{\mathrm{HS}}$	Hydrogen storage price	0.1356	4
$\tilde{\theta}_{\mathrm{inv,EL}}$	EL investment cost	0.1188	5
$\tilde{\theta}_{\mathrm{sub}}$	Government subsidy	0.0876	6
$\tilde{\theta}_{\eta_{\mathrm{FC}}}$	FC efficiency	0.0672	7
$\tilde{\theta}_{\mathrm{inv,FC}}$	FC investment cost	0.0665	8
$\tilde{\theta}_{\mathrm{imb}}$	Imbalance price	0.0603	9
$\tilde{\theta}_{\mathrm{ife,EL}}$	EL lifespan	0.0583	10
$\tilde{\theta}_{\mathrm{HI}}$	Hydrogen incentive	0.0519	11
$\tilde{\theta}_{\mathrm{ife,FC}}$	FC lifespan	0.0509	12
$\tilde{\theta}_{\mathrm{ele}}$	Electricity price	0.0437	13
$\tilde{\theta}_{\eta_{\mathrm{EL}}}$	EL efficiency	0.0376	14

profitable as expected. Increasing EL efficiency is the least profitable improvement.

4.1.1.2. Overview of revenue/cost breakdown. The annual cost and revenue breakdown for all scenarios are illustrated in Fig. 5. The scenarios with $cap_0^{FC} > cap_0^{EL}$ (Fig. 5 (a)) show that the biggest contribution to revenue comes from the sale of more electricity with ΔC^{ele} up to 150 k€/MW$_{\mathrm{WP}}$/year, corresponding to up to 97% of all annual earnings. Particularly, its share in the scenarios with *NPV* > 200 k€/MW$_{\mathrm{WP}}$ is in (86%, 91%), which thus prefers high electricity price and government subsidy. The reduction of imbalance costs ΔC^{imb} is below 16 k€/MW$_{\mathrm{WP}}$/year, contributing up to 84% to the all annual revenue. However, this share is limited to only (9%, 14%) for the high-profit scenarios with *NPV* > 200 k€/MW$_{\mathrm{WP}}$. The O&M costs, mainly due to the hydrogen consumption, are the largest expenditure even up to 112 k€/MW$_{\mathrm{WP}}$/year. Only 27% scenarios are feasible with larger capacity FC, and 18% are below 36 k€/MW$_{\mathrm{WP}}$. The profits more than 100 k€/MW$_{\mathrm{WP}}$ can be achieved in only 1.3% scenarios.

The profits of the scenarios with $cap_0^{FC} < cap_0^{EL}$ (Fig. 5 (b)) is dominated by the sale of hydrogen $\Delta C_j^{\mathrm{hyd}}$ (maximum 116 k€/MW$_{\mathrm{WP}}$/year), which contributes (54%, 91%), (67%, 91%) and (77%, 87%) of the annual income for *NPV* > 100, 200 and 400 k€/MW$_{\mathrm{WP}}$, respectively; while part of the profit is compensated by the expensive hydrogen storage C_j^{HS}, up to 26 k€/MW$_{\mathrm{WP}}$/year and (17%, 93%) of the annual expenditure. Thus, high hydrogen price and low hydrogen storage price is particularly preferred for the scenarios of large EL capacity to be more profitable. Less electricity is sold to power grid under most scenarios (87%) compared with the base cases after using large-capacity EL, because for these scenarios using electricity to produce and sell hydrogen is more rewarding than selling electricity directly. The revenue reduction could be up to 55 k€/MW$_{\mathrm{WP}}$/year, and amounts for at least 30%, 40% and 50% of the annual cost for *NPV* > 100, 200 and 400 k€/MW$_{\mathrm{WP}}$, respectively. Thus, the EL is preferred for low electricity price and government subsidy. Although EL is employed in 78% scenarios, high profits are quite scenario-sensitive: 53% scenarios having *NPV* below 60 k€/MW$_{\mathrm{WP}}$, and the profits within (100, 200), (200, 300), >300 k€/MW$_{\mathrm{WP}}$ are possible in only 7.3%, 1%, and 0.7% scenarios.

4.1.1.3. Quantitative identification of the conditions for high profits. In the following, the distribution of the values of these 14 uncertain parameters are analyzed in detail in Fig. 6. For the scenarios with the FC capacity higher than the EL capacity (Fig. 6 (a)), the maximum *NPV* is 360 k€/MW$_{\mathrm{WP}}$. The FC becomes advantageous with the hydrogen price $\tilde{\theta}_{\mathrm{hyd}}$ below 5.1 €/kg. However, to reach an *NPV* over 100 k€/MW$_{\mathrm{WP}}$, the hydrogen price needs to be below 3.4 €/kg, much lower than the current price 6 €/kg. The standard deviation of WFE $\tilde{\theta}_{\sigma}$ should be higher than 0.04, meaning that the WFEs spread over a large range. The mean value of relative WFEs $\tilde{\theta}_{\mu}$ needs to be over −0.2, thus FC is preferred to reduce large negative deviations (forecasting power > actual power) and the corresponding imbalance costs, particularly when its investment cost is low. The government subsidy $\tilde{\theta}_{\mathrm{sub}}$ and electricity price $\tilde{\theta}_{\mathrm{ele}}$ should be over 17 and 54 €/MWh, respectively, and even higher ($\tilde{\theta}_{\mathrm{sub}}$ > 20

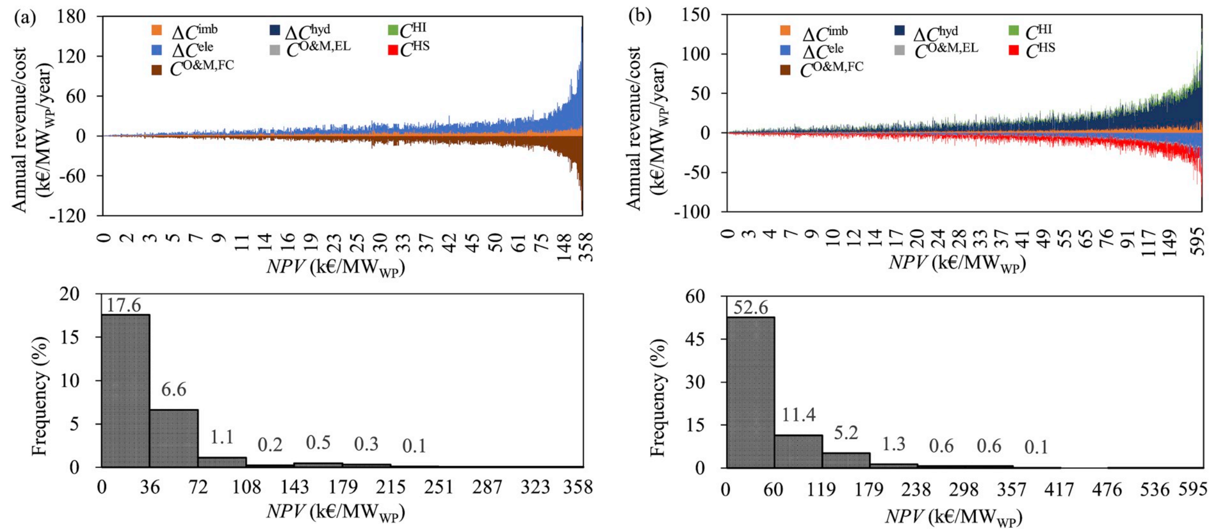

Fig. 5. Revenue/cost breakdown of all scenarios considered in the PHP case: (a) the scenarios with $cap_0^{\mathrm{FC}} > cap_0^{\mathrm{EL}}$, (b) the scenarios with $cap_0^{\mathrm{FC}} < cap_0^{\mathrm{EL}}$.

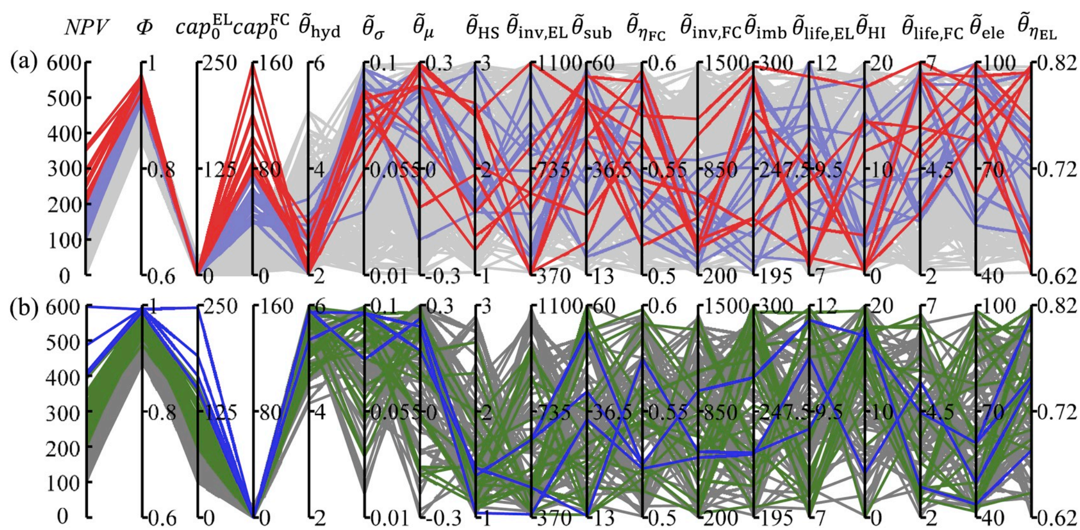

Fig. 6. The distribution of uncertain parameters in all scenarios of the PHP case: (a) the scenarios with $cap_0^{\mathrm{FC}} > cap_0^{\mathrm{EL}}$, (b) the scenarios with $cap_0^{\mathrm{FC}} < cap_0^{\mathrm{EL}}$. The scenarios with NPV in the ranges of (100, 200), (200, 400) and >400 k€/MW$_{\mathrm{WP}}$ are highlighted in different colors. Refer to Table 1 for the units of the parameters. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

€/MWh, $\tilde{\theta}_{\mathrm{ele}} > 63$ €/MWh) for $NPV > 200$ k€/MW$_{\mathrm{WP}}$. A FC efficiency over 50% and an investment cost below 1200 €/kW are necessary for $NPV > 100$ k€/MW$_{\mathrm{WP}}$. The imbalance cost is not the limiting factor to reach $NPV > 100$ k€/MW$_{\mathrm{WP}}$, but for $NPV > 200$ k€/MW$_{\mathrm{WP}}$ it is required to be above 220 €/MWh. The shortest lifespan required for $NPV > 100$ k€/MW$_{\mathrm{WP}}$ is 3.3 years.

For the scenarios with the EL capacity higher than the FC capacity (Fig. 6 (b)), the NPV can reach as high as 600 €/MWh. A high hydrogen price is beneficial to increase the profits of the hybrid systems: over 4.0, 4.6 and 5.3 €/kg for $NPV > 100$, 200 and 400 k€/MW$_{\mathrm{WP}}$, respectively. Higher standard deviation of WFE ($\tilde{\theta}_{\sigma}$) is preferred to reach higher NPV: 0.020, 0.036, 0.077 for $NPV > 100$, 200, 400 k€/MW$_{\mathrm{WP}}$, respectively. High profit from the EL is more likely when the WFEs spread over a large range. The range of $\tilde{\theta}_{\mu}$ is (−0.18, 0.29) for $NPV > 200$ k€/MW$_{\mathrm{WP}}$, and is further narrowed to (0.17, 0.26) for $NPV > 400$ k€/MW$_{\mathrm{WP}}$. The lower bound is increased because the EL gets more profit under larger positive deviations (forecasting power < actual power); while the upper bound is decreased, since reducing very large positive deviations ($\tilde{\theta}_{\mu} > 0.27$) requires large capacity of the EL leading to considerable investment cost. The hydrogen storage price $\tilde{\theta}_{\mathrm{HS}}$ is slightly limited to below 2.6 €/kg for $NPV > 200$ k€/MW$_{\mathrm{WP}}$ and below 1.5 €/kg for $NPV > 400$ k€/MW$_{\mathrm{WP}}$. The investment costs $\tilde{\theta}_{\mathrm{inv,\,EL}}$ need to be below at least 960, 640 €/kW for $NPV > 200$ and 400 k€/MW$_{\mathrm{WP}}$. The government subsidy ($\tilde{\theta}_{\mathrm{sub}}$), imbalance price ($\tilde{\theta}_{\mathrm{imb}}$), lifespan of EL ($\tilde{\theta}_{\mathrm{life,EL}}$), hydrogen incentive ($\tilde{\theta}_{\mathrm{HI}}$), electricity price ($\tilde{\theta}_{\mathrm{ele}}$) and efficiency of EL ($\tilde{\theta}_{\eta_{\mathrm{EL}}}$) are not clustered for $NPV > 200$ k€/MW$_{\mathrm{WP}}$; however, they become important when pursuing higher $NPV > 400$ k€/MW$_{\mathrm{WP}}$: $\tilde{\theta}_{\mathrm{sub}} < 55$ €/MWh, $\tilde{\theta}_{\mathrm{ele}} < 60$ €/MWh, $220 < \tilde{\theta}_{\mathrm{imb}} < 250$ €/MWh, $\tilde{\theta}_{\mathrm{HI}} > 4.2$ €/MWh are needed. In addition, an EL lifespan of over 9 years and an efficiency over 68% are necessary.

4.1.2. The lithium battery case

4.1.2.1. Overview of all scenarios and the key influential uncertain parameters.

The optimal capacity of lithium battery (cap_0^{LB}) and corresponding reliability Φ of all 1800 scenarios are shown in Fig. 7. The largest revenue is 307 k€/MW$_{\mathrm{WP}}$ with 76 kW h/MW$_{\mathrm{WP}}$ lithium battery under the scenario $\boldsymbol{\theta} = \{75.3, 46.8, 269.8, 244, 0.71, 0.28, 0.088\}$. Unfortunately, lithium battery can be profitable (with $NPV > 0$) for only

24% scenarios and is not feasible under most scenarios from economic perspective. The maximum storage capacity identified is 88 kW h/MW$_{WP}$ with an *NPV* of 144 k€/MW$_{WP}$ under the scenario $\tilde{\boldsymbol{\theta}} = \{73.5, 18.3, 212.3, 253, 0.68, 0.25, 0.010\}$. For the profitable scenarios, the reliability Φ is over 0.57 and up to 0.94, higher than that of the base case (0.57, 0.85) under the same scenarios.

The factor prioritization of uncertain parameters profit is shown in Table 3. Investment cost $\tilde{\theta}_{\text{inv,LB}}$ is the single very influential factor, followed by the allowable DOD. The influence of the remaining factors, i.e., government subsidy $\tilde{\theta}_{\text{sub}}$, wind power prediction $\tilde{\theta}_{\sigma}$ and $\tilde{\theta}_{\mu}$, the imbalance price $\tilde{\theta}_{\text{imb}}$, electricity prices $\tilde{\theta}_{\text{ele}}$, which can be important for the PHP cases, become very limited.

The *NPV* decreases dramatically along the increase in the investment cost of LB as shown in Fig. 8 (a). The median *NPV* for the battery price below 347 €/kWh is 45 k€/MW$_{WP}$. It decreases down to only 10 k€/MW$_{WP}$ when the battery price is within the range of (347, 484) €/kWh. The median *NPV* is zero if the battery price is over 484 €/kWh.

It is not profitable to use LB with the depth of discharge $\tilde{\theta}_{\text{DOD}}$ below 75% (A in Fig. 8 (b)) if the investment is more than 540 €/kWh, and the interval is increased to 83% when the investment cost is higher than 700 €/kWh (B in Fig. 8 (b)), since it will require a large capacity to address the same scale of imbalance with a substantial increase in the investment cost. When the DOD is between (0.7, 0.85), the battery case is able to earn profits more than 200 k€/MW$_{WP}$. However, a further increase in the DOD leads to a decrease in *NPV*, due to its negative effects on the battery lifetime (Eq. (11)), leading to an increase in battery replacement costs (as a part of the investment costs). In the scenarios operating DOD in (0.9, 1), most of them (86%) should install battery lower than 20 kW h/MW$_{WP}$, which is far below the maximum battery capacity (88 kW h/MW$_{WP}$).

4.1.2.2. Revenue/cost breakdown. The breakdown of annual revenue of all scenarios is given in Fig. 9. The annual investment cost includes both the initial investment costs and the replacement costs. With LB, the sale of the stored excess electricity can earn (11, 39) and (22, 39) k€/MW$_{WP}$/year for the scenarios with *NPV* > 100 and 200 k€/MW$_{WP}$, contributing the biggest part (62%, 86%) and (64%, 78%) of annual income. Thus, higher electricity price and government subsidy increase the feasibility of implementing LB ($\tilde{\theta}_{\text{sub}} > 15$ €/kWh and $\tilde{\theta}_{\text{ele}} > 57$ €/MWh for *NPV* > 200 k€/MW$_{WP}$). The reduction of the imbalance costs is within (3, 18) and (9, 18) k€/MW$_{WP}$/year for *NPV* > 100 and 200 k€/MW$_{WP}$, accounting for (14%, 38%) and (22%, 36%) of the annual income. In 24% feasible scenarios, 13% scenarios have *NPV*less than 31 k€/MW$_{WP}$, and 6% are within (31, 61) k€/MW$_{WP}$; while only 3% scenarios have profits more than 100 k€/MW$_{WP}$.

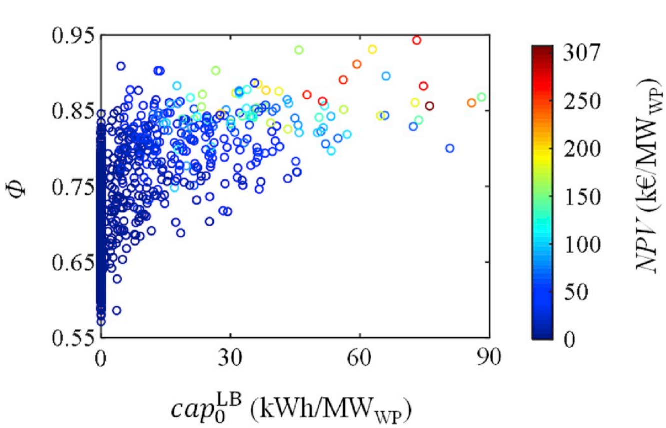

Fig. 7. The $cap_0^{\text{LB}}$and Φ corresponding to the maximum *NPV*under each scenario of the LB case.

Table 3
Factor prioritizations of uncertain parameters for the LB case.

Uncertain inputs	Description	Sensitivity index *sk*	Rank
$\tilde{\theta}_{\text{inv,LB}}$	LB investment cost	0.2950	1
$\tilde{\theta}_{\text{DOD}}$	Allowable DOD interval	0.0013	2
$\tilde{\theta}_{\text{sub}}$	Government subsidy	−0.013	3
$\tilde{\theta}_{\sigma}$	Standard deviation of WFEs	−0.013	4
$\tilde{\theta}_{\text{imb}}$	Imbalance price	−0.028	5
$\tilde{\theta}_{\text{ele}}$	Electricity price	−0.032	6
$\tilde{\theta}_{\mu}$	Expected value of WFEs	−0.038	7

4.1.2.3. Quantitative identification of the conditions for high profits. The scenarios with *NPV* over 100 k€/MW$_{WP}$ are further highlighted in Fig. 10 to quantify the conditions of using LB. The investment cost ($\tilde{\theta}_{\text{inv,LB}}$) is required to be below 760 €/kWh to be profitable, and below 510 and 300 €/kWh for *NPV* > 100 and 300 k€/MW$_{WP}$, which are far below the current price (1500 €/kWh). The $\tilde{\theta}_{\text{DOD}}$ is clustered within (63%, 98%) for *NPV* >100 k€/MW$_{WP}$, and (68%, 88%) for *NPV* > 200 k€/MW$_{WP}$. The standard deviation of WFEs ($\tilde{\theta}_{\sigma}$) is required to be higher than 0.04 for *NPV* > 100 k€/MW$_{WP}$ and over 0.063 for *NPV* > 200 k€/MW$_{WP}$. The imbalance price $\tilde{\theta}_{\text{imb}}$ should be over 210 €/MWh for *NPV* > 100 k€/MW$_{WP}$. The ranges of mean value of WFEs ($\tilde{\theta}_{\mu}$) for *NPV*> 100 and 200 k€/MW$_{WP}$ are (−0.11, 0.3), (0.17, 0.28), meaning that the LB is more profitable when the magnitude of positive deviations is higher than that of negative deviations, since enough electricity should be stored during positive deviations before releasing for decreasing imbalance cost.

It should be noted that the threshold investment cost of LB is 760 €/kWh, considering various uncertain parameters. This number is much higher than 105 €/kWh obtained in Ref. [24] which investigated a 400 kW h/MW$_{WP}$ battery under only two uncertain parameters (electricity price and DOD) [24]. The extremely-low investment cost requirement is caused by using a fixed, large battery capacity (400 kW h/MW$_{WP}$), which is, however, suggested to be no more than 88 kW h/MW$_{WP}$ as mentioned above in Fig. 7.

4.2. Comparison of the two cases

The PHP and LB cases are further compared comprehensively considering the economy, reliability, equivalent full load hours, lost wind and environmental sustainability. Regarding profit and reliability in Fig. 11, the PHP case is economically-feasible in most of the scenarios (98.6%) with the profit up to 600 k€/MW$_{WP}$; while the LB is only feasible in 24% scenarios with over 80% of them below 100 k€/MW$_{WP}$. The feasibility and profit of the LB case is limited by the high investment cost as shown in Fig. 10; while positive *NPV* is possible in the PHP case under almost all scenarios investigated and favorable scenarios with high hydrogen price, cheap hydrogen storage, large magnitude of positive WFEs make profit from EL up to 600 k€/MW$_{WP}$ feasible (as shown in Fig. 6). The reliability of the PHP case is (0.62, 0.99), higher than that of the LB case (0.57, 0.94). High reliability requires large-capacity storage as shown in Figs. 4 and 7. However, large-capacity LB is not preferred due to the high investment cost. From these two criteria, the PHP case is potentially better than the LB case.

The equivalent full-load hours of the FC, EL, and LB are within (1124, 5951), (2221, 6385) and (1091, 3981) hours, respectively, with the frequency distribution shown in Fig. 12. The EL tends to be used more than FC and LB: 78% scenarios over 3700 h, 36% scenarios over 4380 h. However, only 3% scenarios utilize the FC over 4380 h and such heavy use of battery does not occur. The FC could be heavily used unless wind farms submit a high dispatched power (P_{disp} in Fig. 2), but the high dispatched power might accompany with considerable imbalance cost, thus the heavy use of FC is not preferred. However, this constraint

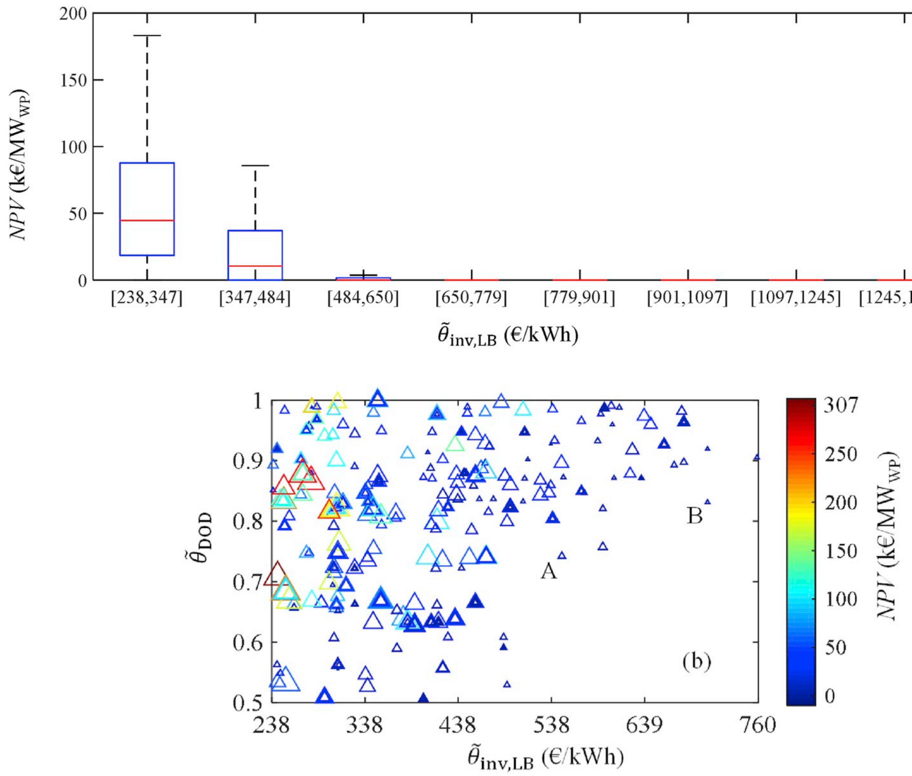

Fig. 8. Influence of the investment cost and allowable depth of discharge of the LB (without outliers). In (b), the sizes of marks reflect the optimal battery capacities.

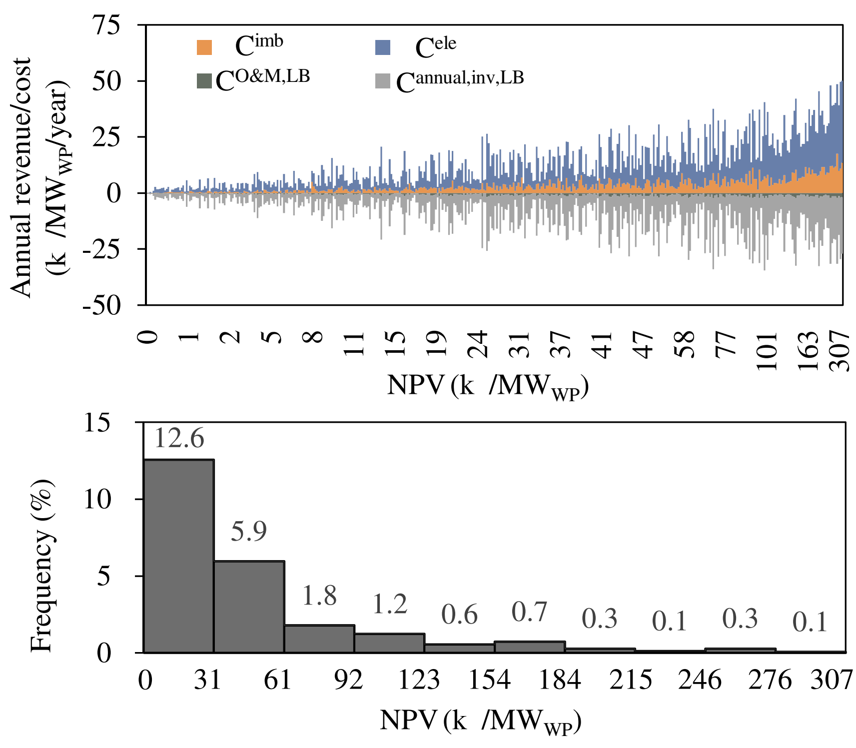

Fig. 9. Revenue breakdown of all scenarios considered in the LB case.

enhances the utilization of EL. The DOD of the LB is suggested to be not fully charged/discharged (Fig. 10) for prolonging the lifespan, which results in the low equivalent full-load hours of LB, proven by the full load hours always more than 3000 h (85%) when the DOD is up to 0.9.

The frequency distributions of lost wind rate of the two cases are shown in Fig. 13. Lost wind rate of the PHP case ranges from 0.04% to

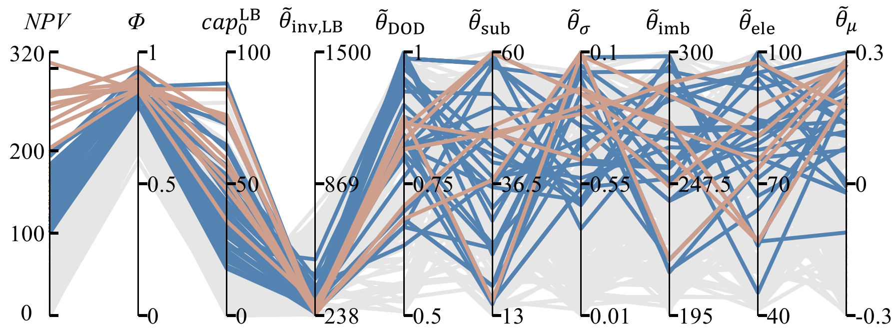

Fig. 10. The clustering of uncertain parameters of the LB case for the scenarios with positive *NPV* (k€/MW_{WP}). Refer to Table 1 for the units of the uncertain parameters.

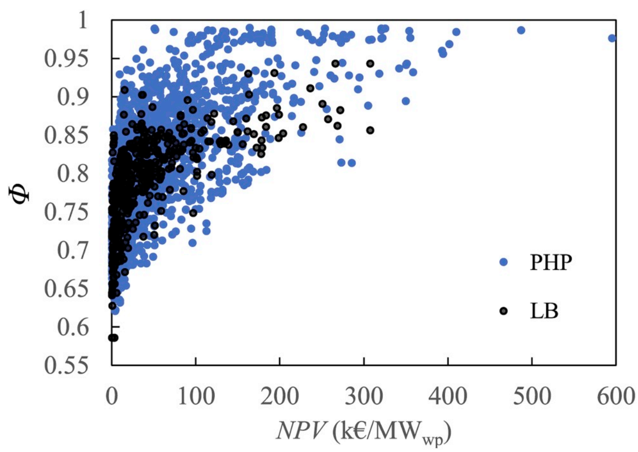

Fig. 11. The *Φ* and *NPV* of the PHP and LB cases.

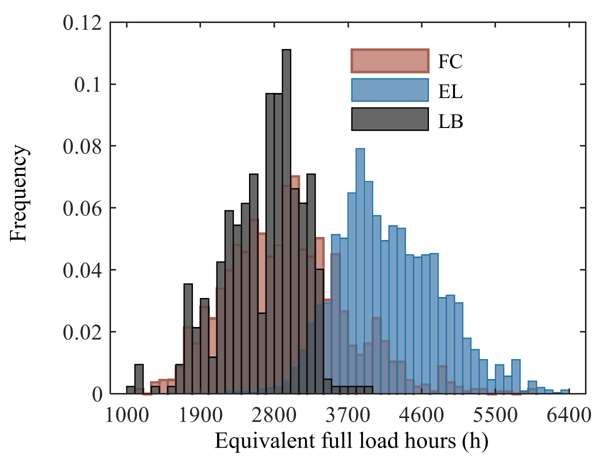

Fig. 12. Equivalent full-load hours of FC, EL and LB in all scenarios investigated.

9.4%, and the rate is below 2% under 60% scenarios. Using the LB, the lost wind rate is below 8% and 81% scenarios lost wind less than 2%. The lost wind rate will be decreased after using FC, because wind farms tend to submit a higher dispatched power than the base case (referring to Fig. 2). However, the lost wind is not always reduced as increasing EL capacity, because the EL might not be able to completely store the addition lost wind after submitting a lower dispatched power compared with the base case, especially the revenues from hydrogen sale and reducing imbalance cost become not advantageous enough. The lost wind rates under different FC and EL capacities are shown in Fig. A 1.

The environmental sustainability of the two cases are also assessed and compared. There have been several methods available, e.g., life cycle assessment [49] or exergoenvironmental analysis [50–52] by combining exergy analysis. However, the latter is not employed due to limited benefits for the system investigated. The main environmental impact considered is the greenhouse gas (GHG) emissions (global warming potential in kg carbon dioxide equivalents). The GHG emissions comes mainly from two aspects: manufacture of equipment (EL, FC and LB) and the hydrogen purchased from the market, whose production is currently dominated by steam methane reforming of natural gas. The environmental impact from the wind farm is not considered since both cases involve the same wind farms. The emission of manufacturing 1 kW FC and 1 kW h LB is 37 [53]and 166 [54] kg $CO_{2\,eq}$, while producing 1 kg hydrogen via methane reforming discharges 8.9 kg $CO_{2\,eq}$ [55]. The maximum GHG emissions of the PHP case with higher FC, the PHP case with higher EL, and the LB case are 105, 19 and 4 kg $CO_{2\,eq}$ per MWh electricity sent to the grid, with the frequency given in Fig. 14. The GHG impacts of the LB case can be ignored with the emission of 60% scenarios below 1 kg $CO_{2\,eq}$/MWh. The PHP cases with higher EL (95% scenarios below 5 kg $CO_{2\,eq}$/MWh for) perform better than the cases with higher FC (only 60% scenarios below 5 kg $CO_{2\,eq}$/MWh), which is due to the significant contribution of the hydrogen purchased from the market for the FC.

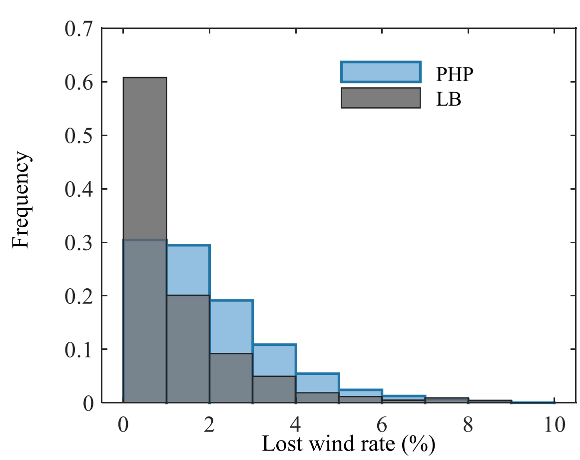

Fig. 13. Frequency distribution of lost wind rate of both the PHP and LB cases.

5. Conclusions

In this paper, the feasibility of power-to-hydrogen-to-power and lithium battery in reducing the impacts of wind forecasting errors was assessed under uncertain parameters via statistical optimal sizing and investigated factor prioritizations by global sensitivity analysis method. Uncertain market prices (electricity, hydrogen trade and storage, imbalance, government incentive), storage technology (investment cost, efficiency and lifespan) and wind forecasting performance were evaluated. Major conclusions are as follows:

- The profit of the power-to-hydrogen-to-power case is sensitive to the hydrogen price, wind forecasting accuracy and hydrogen storage price. Decreasing electrolyzer's investment cost might be the most potential technological development compared with prolonging lifespans and increasing efficiencies.
- Under low hydrogen price, fuel cell is not competitive enough even with an investment cost as low as 200 €/kWh and does not help to achieve high profits. To reach a profit >100 k€/MW_{WP} (only in 1.3% scenarios), hydrogen price needs to be below 3.4 €/kg, while government subsidy, electricity price and lifespan should be over 17 €/MWh, 54 €/MWh and 3.3 years.
- Electrolyzer is more advantageous than fuel cell to achieve high profits, particularly with high hydrogen price, low hydrogen storage price and investment cost. To achieve a profit >100 k€/MW_{WP} (in 9% scenarios), the hydrogen price should be up to 4.0 €/kg; while for a profit >200 k€/MW_{WP}, the hydrogen price needs to be up to 4.6 €/kg, and hydrogen storage and investment cost below 2.6 €/kg and 960 €/kW.
- For lithium battery case, decreasing battery investment cost is the most important, since investment cost is the single highly influential factor, which should be below 760 €/kWh. The battery capacity is limited to 88 kW h/MW_{WP}. A profit over 100 k€/MW_{WP} is possible for 3% scenarios with the investment cost below 510 €/kWh and the depth of discharge in (63%, 98%).
- The power-to-hydrogen-to-power case is more advantageous in terms of profitability, reliability and utilization factor (full-load operating hours), while lithium battery is more helpful to reduce lost wind and has less environmental impact. The power-to-hydrogen-to-power can bring profits in 98% scenarios and might increase the reliability up to 0.99, with the electrolyzer used over 3700 h (78% scenarios). Lithium battery makes lost wind rates below 2% in 81% scenarios.

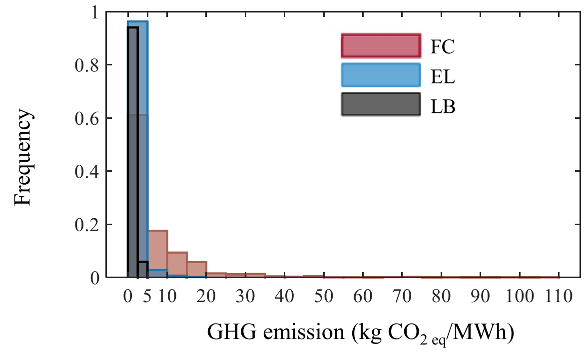

Fig. 14. Frequency distribution of GHG emission of PHP case with higher EL, higher FC and LB case.

There are several limitations of the current model to be improved. Firstly, the uncertain parameters are assumed to be independent from each other, which may be inconsistent with the reality. Secondly, the ranges of uncertain parameters affect the factor prioritizations. Future work will investigate other promising onsite storage technologies, especially reversible or unitized fuel cell systems and flow battery, as well as hybrid storage systems.

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Appendix

Table A 1
Review of sensitivity and uncertainty analysis to wind-storage hybrid system

ESS	Applications	Methods	Uncertain parameters									Reference
			Investment cost	Efficiency	Lifespan	Capacity	Electricity price	Imbalance price	Government subsidy	WFE	Fuel price	
Battery	Balancing wind power fluctuation	LSA	✓	✓	✓	✓				✓		[4]
PHP	Balancing wind power fluctuation and providing secondary control reserve	LSA (scenarios)				✓						[11]
EL	Producing hydrogen by EL	LSA				✓						[17]
PHP	Balancing wind power fluctuation	LSA (scenarios)	✓				✓	✓	✓		✓	[18]
FC		LSA			✓							[19]

(continued on next page)

Table A 1 (*continued*)

ESS	Applications	Methods	Uncertain parameters									Reference
			Investment cost	Efficiency	Lifespan	Capacity	Electricity price	Imbalance price	Government subsidy	WFE	Fuel price	
	Supplying residential electricity and heat											
LB	Primary Frequency Regulation	LSA			✓							[21]
LB	Balancing wind power fluctuation	LSA	✓		✓	✓						[24]

Table A 2
Calculations of electricity (MWh)

Items	Description	Equations
$W_j^{\text{cha,ESS}}$	Electricity charge to ESS	$\int_0^G f_{\text{Weibull}}(P)\left(\int_{\delta_{\text{disp}}}^{\delta_{\max}}\left(\frac{P}{1-\delta}-P_{\text{disp}}\right)f_{\text{Gauss}}(\delta)d\delta+\int_{\delta_{\max}}^{1} cap_0^{\text{EL}}f_{\text{Gauss}}(\delta)d\delta\right)dP$
$W_j^{\text{dis,ESS}}$	Electricity discharge from ESS	$\int_0^G f_{\text{Weibull}}(P)\left(\int_{-\infty}^{\delta_{\min}} cap_0^{\text{FC}}f_{\text{Gauss}}(\delta)d\delta+\int_{\delta_{\min}}^{\delta_{\text{disp}}}\left(P_{\text{disp}}-\frac{P}{1-\delta}\right)f_{\text{Gauss}}(\delta)d\delta\right)dP$
W_j^{wind}	Wind electricity sold to grid	$\int_0^G f_{\text{Weibull}}(P)\left(\int_{-\infty}^{\delta_{\text{disp}}}\frac{P}{1-\delta}f_{\text{Gauss}}(\delta)d\delta+\int_{\delta_{\text{disp}}}^{1} P_{\text{disp}}f_{\text{Gauss}}(\delta)d\delta\right)dP$
W_j^{imb}	Imbalanced electricity	$\int_0^G f_{\text{Weibull}}(P)\left(\int_{-\infty}^{\delta_{\min}}\left(P_{\text{disp}}-\frac{P}{1-\delta}-cap_0^{\text{FC}}\right)f_{\text{Gauss}}(\delta)d\delta\right)dP$

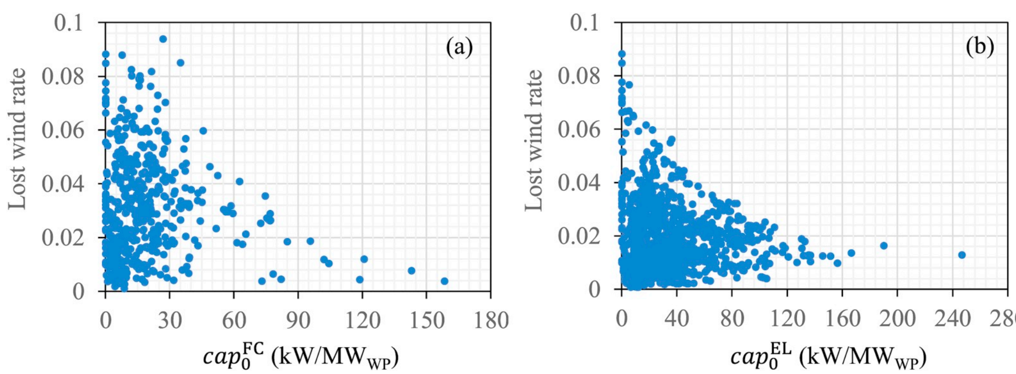

Fig. A 1. Lost wind rates of PHP cases: (a) wind farms install FC (b) wind farms install EL.

Nomenclatures

Abbreviations

ALE	alkaline
$CO_{2\ eq}$	carbon dioxide equivalent
DOD	depth of discharge
EL	electrolyzer
ESS	energy storage system
FC	fuel cell
GHG	greenhouse gas
GSA	global sensitivity analysis
LB	lithium battery
LHV	lower heating value
LSA	local sensitivity analysis
NPV	net present value
O&M	operation and maintenance
PEM	polymer electrolyte membrane
PHP	power-to-hydrogen-to-power
RMSR	root mean square error
TSO	transmission system operator
WFE	wind forecasting error

Mathematical symbols

C	cost/revenue
cap	capacity
E	expected value
f	distribution probability density
g	sizing optimization model
i	discount rate
l	the number of scenarios
m	the number of uncertain parameters
N	the number of samples for global sensitivity analysis
$\overline{P}$	actual wind power
P	forecasting wind power
rep	replacement
S	importance index of uncertain parameters
V	variance
W	electricity
$\boldsymbol{x}$	a random combination of uncertain parameters
γ	shape parameter of Weibull distribution
β	scale parameter of Weibull distribution
δ	relative wind forecasting error
σ	standard deviation of Gaussian distribution
μ	expected value of Gaussian distribution
$\tilde{\theta}$	uncertain parameter
τ	lifespan of wind farms
η	energy efficiency
Δ	difference from base case
Φ	probability of generating dispatched power

Subscripts/Superscripts

cha	charge
dis	discharge
disp	dispatch
ele	electricity
HS	hydrogen storage
hyd	hydrogen
imb	imbalance
inv	investment cost
j	index of years
k	index of uncertain parameters
rep	replacement
sub	subsidy
WP	wind power

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