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Whole system value of long-duration electricity storage in systems with high penetration of renewables

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ABSTRACT

Energy storage is a key enabling technology to facilitate an efficient system integration of intermittent renewable generation and support energy system decarbonisation. However, there are still many open questions regarding the design, capacity, and value of long-duration electricity storage (LDES), the synergy or competition with other flexibility technologies such as demand response, short-duration storage, and other forms of energy storage such as hydrogen storage. This paper presents a novel integrated formulation of electricity and hydrogen systems to identify the roles and quantify the value of long-duration energy storage holistically. A spectrum of case studies has been performed using the proposed approach on a future 2050 net-zero emission system background of Great Britain (GB) with a high share of renewable generation and analysed to identify the value drivers, including the impact of prolonged low wind periods during winter, the impact of different designs of LDES, and its competitiveness and synergy with other technologies. The results demonstrate that high storage capacity can affect how the energy system will evolve and help reduce system costs.

KEYWORDS

Long-duration energy storage (LDES), whole-system optimisation, integrated electricity-hydrogen system.

Meeting the zero-emission target cost-effectively would require a significant capacity of low carbon generation. Some capacities will need to be firm and controllable to balance the variability and intermittency of renewable energy and minimise emissions while maintaining system security. Moreover, the United Kingdom (UK) meteorological studies[1] demonstrate a correlation between extreme cold conditions with low wind output. Such events can occur for a relatively long period (a few days to weeks). In these conditions, firm low-carbon generation technologies such as nuclear, hydrogen-based generation, and thermal plants with carbon capture and storage (CCS) are important to keep the residual emissions low. However, those technologies are more expensive than large-scale wind and photovoltaics (PV), leading to higher system costs. Alternatively, the system could have large-scale, long-duration energy storage to solve the supply and demand balancing issues in a system with high renewable energy sources (RES).

There are still many open questions regarding the design, capacity, and the value of long-duration electricity storage, the synergy or competition with other flexibility technologies such as demand response, short-duration storage, and other forms of energy storage such as hydrogen and thermal storage. For example, as an alternative to electricity storage, hydrogen storage can store excess electricity, e.g., during periods of high-RES output, after being converted to hydrogen by electrolysers ("power-to-gas"). While during periods of low output of RES, the stored hydrogen can be used as fuel to generate electricity.

Identifying the optimal energy storage portfolio requires locations and technology-specific techno-economical characteristics, e.g., costs, ramping capability, ability to provide response and reserve services, and efficiency losses to be considered. For example, long-duration pumped hydro energy storage (LD-PHES) round-cycle efficiency is c. 75%, while using hydrogen storage for electricity generation later yields much lower efficiency, around 40%–50%.

Quantifying the system benefits of storage technologies needs to consider two key aspects: time horizons and interactions across different assets, technologies, and subsystems. Capturing long-term investment-related time horizon to real-time balancing on a second-by-second scale is important as storage technologies can contribute to generation and network investment savings and increase system operation efficiency. Storage can also affect the system needs for other technologies (generation, network, and other flexibility resources) depending on their locations, designs, and technologies. In this context, this paper describes an approach to analyse the role and quantify the value of long-duration electricity storage (LDES) in facilitating a cost-effective transition to a low-carbon energy system.

1 State-of-the-art review

Initial research on the value of storage for integrating intermittent renewable generators primarily focused on the capability of storage to perform arbitrage[2] or provide reserve[3] in systems characterised by high penetration of intermittent generation. In that respect, a framework for assessing storage's benefits and market potential for utility-related applications was outlined in ref. [4]. Specific uses of energy storage systems to manage the output variability of wind and solar generation were addressed in refs. [5, 6]. Stochastic approaches to valuation of storage for arbitrage and reserve, such as the one provided in ref. [7], were used to study storage value in systems with large shares of wind generation. Previous work investigated some different storage technologies and their potential applications, such as stochastic optimisation of

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pumped-storage units[8] or compressed air energy storage[9] to support market participation of wind generation; grid-scale application of batteries[10]; or sizing and control of flow batteries[11]. Reliability benefits of energy storage in a system with high wind penetration, including the improvement of wind capacity credit, were quantified in refs. [12, 13], while the problem of optimal sizing of storage systems was addressed in refs. [14, 15]. The potential of storage to contribute simultaneously to both energy markets and frequency regulation was evaluated in refs. [16, 17].

Several approaches have been developed to understand the economic benefit of long-duration energy storage: (1) net-load analysis to estimate the storage capacity needed to cover periods with over generation or insufficient generation[18]; (2) time-series optimisation with enhanced reduced modelling datasets to allow energy storage investment evaluation[19–21]; (3) stochastic optimisation to consider uncertainty in RES and load forecasting[8,22]; (4) sequential market and operation model to capture market-driven storage cycle across long-period[23]. However, it is worth noting that most of the studies focused on electricity systems only and did not evaluate the impact of the prolonged low RES output and competition across different technologies such as short-duration storage or demand-side response. Techno-economic enclosed analyses of different LDES technologies in combination with flexible power generation were discussed in ref. [24] to estimate the levelized cost of energy of various technologies; as a means to compare different technologies while ref. [25] analysed offgrid applications. However the value of LDES on whole-energy system was not considered fully (e.g., impact on the investment of energy production, network, carbon storage, and removal capacity).

Addressing the gaps above, the contribution of this paper is twofold. First, this paper presents a novel integrated electricity and hydrogen systems optimisation model to evaluate and valorise long-duration energy storage system contribution. The model simultaneously optimises investments in energy supply capacity, energy network, energy storage while minimising short-term system operation cost through hourly system operation representation while considering energy system balancing requirements. System adequacy and security requirements, together with emission constraints, are also considered within the same framework. The model further includes a detailed representation of electricity demand and considers the capability of demand response technologies, using the inputs supplied by detailed bottom-up demand models. Second, the paper shows the impact of different storage designs, prolonged low RES output through the implementation of different RES profiles, and competition with short-term flexibility on the value of long-duration electricity storage.

2 Problem formulation

Due to a great variety of different storage technology parameters, a technology-agnostic approach has been adopted in this paper where no particular choice is made concerning storage technology. The objective is rather to assess the system value of storage represented through generic parameters (power rating, duration, efficiency, installation cost, among others) while varying the value of these parameters in a rather broad range in order to cover a wide variety of storage technologies potentially available in the future.

The whole-electricity system model[26] has been expanded to include a hydrogen system. The integration of hydrogen and power system is important[27] as low-carbon power generation technologies and hydrogen will be the two main clean energy sources in the future. The problem is formulated as a large-scale linear programming problem with a time horizon of 1 year and hourly time resolution and solved simultaneously. The nomenclature for this problem formulation can be found in the Appendix.

The objective function (1) minimises the overall system cost, consisting of annuitised investment costs associated with various energy production, network and storage assets, and the annual operating cost for electricity (2) and hydrogen systems (3) plus the cost of greenhouse gas removal to meet the carbon target. The investment cost includes (annuitised) the capital cost of new energy production capacity, storage units, and additional energy network capacity. Various types of investment costs are annuitised using the appropriate weighted-average cost of capital (WACC) and the estimated economic life of the asset. Both of these parameters are provided as inputs to the model for each technology.

$$Minimise\ \phi = C_e + C_h + C_{ghr}\, ghr \tag{1}$$

where
cost of electricity system:

$$C_e = \sum_{i=1}^{G} \pi_{\hat{\mu}_i}.\hat{\mu}_i + \sum_{i=1}^{S} \pi_{\hat{s}_i}.\hat{s}_i + \sum_{i=1}^{F} \pi_{\hat{f}_i}.\hat{f}_i + \sum_{t=1}^{T}\sum_{i=1}^{G} C_{g_i}^{\,t}(\pi_{g_i}, g_i^t, \pi_{nl\,i}, \pi_{st\,i}, \mu_i^t) \tag{2}$$

cost of hydrogen system:

$$C_h = \sum_{i=1}^{H} \pi_{\hat{h}_i}.\hat{h}_i + \sum_{i=1}^{E} \pi_{\hat{e}_i}.\hat{e}_i + \sum_{i=1}^{Sh} \pi_{\widehat{Sh}_i}.\widehat{Sh}_i + \sum_{i=1}^{Fh} \pi_{\widehat{fh}_i}.\widehat{fh}_i + \sum_{t=1}^{T}\sum_{i=1}^{H} C_{h_i}^{\,t}(\pi_{h\,i}, h_i^t) \tag{3}$$

Electricity system operating cost is the total annual generation cost that consists of (i) variable cost, which is a function of electricity output, (ii) no-load cost, which is a function of synchronised units, and (iii) start-up cost, while hydrogen system operating cost is associated with the hydrogen production cost from gas.

There are a set of equality and inequality constraints that the model takes into account while minimising the overall cost. All constraints are applied for each time interval within the optimisation time horizon ($\forall t \in T$). These include:

2.1 Power system constraints

Power balance constraints (4) ensure that supply and demand, taking into account storage and DSR, are balanced at all times.

$$\sum_{i=1}^{G} g_i^t + \sum_{i=1}^{S} (s_{+i}^t - s_{-i}^t) - \sum_{i=1}^{D} (\mathrm{d}_i^t + d_{+i}^t - d_{-i}^t) - \sum_{i=1}^{E} e_i^t = 0 \tag{4}$$

Generator operating constraints include (i) minimum stable generation (MSG) and maximum output constraints (5); (ii) ramp-up (6) and ramp-down (7) constraints; (iii) minimum up (8) and downtime (9) constraints; (iv) available frequency response and reserve constraints (10); maximum response constraints for each generation technology (11); annual load factor constraints (12); and the maximum number of synchronised units (13). Constraints (5)–(13) are applied to all generators ($\forall i \in G$).

$$\mu_i^t.\underline{\mathrm{g}}_i \le g_i^t \le \mu_i^t.\overline{\mathrm{g}}_i \tag{5}$$

$$g_i^t - g_i^{t-1} \le \mu_i^t.\mathrm{r}_{up\,i} \tag{6}$$

$$g_i^{t-1} - g_i^t \le \mu_i^{t-1} \cdot \mathrm{r}_{dn\,i} \tag{7}$$

$$\sum_{k=t-\underline{\mathrm{Up}}_i}^{t-1} st_i^k \le \mu_i^t \tag{8}$$

$$\mu_i^t \leq \overline{\mu}_i + \widehat{\mu}_i - \sum_{k=t-\mathrm{Dn}_i}^{t-1} ds_i^k \tag{9}$$

$$\mu_i^t \cdot \underline{g}_i \leq g_i^t + rsp_i^t + res_i^t \leq \mu_i^t \cdot \overline{g}_i \tag{10}$$

$$rsp_i^t \leq \mu_i^t \cdot \overline{\mathrm{rsp}}_i \tag{11}$$

$$\sum_{t=1}^{T} g_i^t \leq \mathrm{LF}_i \cdot \tau \cdot (\overline{\mu}_i + \widehat{\mu}_i) \cdot \overline{g}_i \tag{12}$$

$$\mu_i^t \leq \overline{\mu}_i + \widehat{\mu}_i \tag{13}$$

The model optimises both the quantity and the location of new generation capacity for various generation technologies. If required, constraints can be put in place to limit the investment in particular generation technologies at given locations. Annual load factor constraints (12) can be used to limit the utilisation level of thermal generating units, e.g. to account for the effect of planned annual maintenance on plant utilisation.

Storage operating constraints include maximum power rating constraints for storage charging (14) and discharging cycles (15); constraints associated with the amount of energy that can be stored (16); and the storage energy balance (17). The model considers new investments in energy storage by optimising its location and capacity to minimise the overall cost (2). Constraints (14)–(17) are applied to all storage units ($\forall i \in S$).

$$s_{+i}^t \leq \overline{s}_i + \widehat{s}_i \tag{14}$$

$$s_{-i}^t \leq \overline{s}_i + \widehat{s}_i \tag{15}$$

$$es_i^t \leq (\overline{s}_i + \widehat{s}_i) \cdot \mathrm{sc}_i \tag{16}$$

$$es_i^t = es_i^{t-1} - s_{+i}^t + \eta_{si} \cdot s_{-i}^t \tag{17}$$

Demand-side response constraints include constraints for various specific types of loads. Different demand categories are associated with different levels of flexibility. Flexibility parameters associated with various forms of DSR are obtained using detailed bottom-up modelling of different types of flexible demand. A set of generic DSR constraints is presented below. These include the demand reduction constraints (18) and the energy balance for demand shifting (19), potentially considering losses driven by a temporal shifting of demand (as shifting demand may increase the overall energy requirements), quantified through the efficiency η_d. Constraints (18)–(19) are applied to all electricity loads ($\forall i \in D$).

$$d_{-i}^t \leq \alpha_{d_i}{}^t \cdot \mathrm{d}_i^t \tag{18}$$

$$\sum_{t \in D_x} d_{-i}^t \leq \eta_{di} \cdot \sum_{t \in D_x} d_{+i}^t \tag{19}$$

Operating reserve constraints include various forms of fast and slow reserve constraints. The operating reserve and frequency response requirements are calculated exogenously as a function of uncertainty in variable generation and demand across various time horizons. Deterministic renewable energy profiles and a predefined forecast error level (e.g. 5%) for additional operating reserve requirements due to variable renewable sources are used while the frequency response requirement is calculated based on the impact of the largest loss of infeed in different system inertia conditions[28]. The model distinguishes between two key types of balancing services: (i) frequency regulation (response), which is delivered in the timeframe of a few seconds to 30 minutes; and (ii) reserve, typically split between spinning and standing reserve, with delivery occurring within the timeframe of half an hour to several hours after the request. Wind output forecasting errors directly drive the need for these services, which will significantly affect the ability of the system to absorb wind energy. The reserve and response requirements calculation for a given level of intermittent renewable generation is carried out exogenously and fed into the model.

The frequency response and reserve constraints are formulated in (20) and (21), respectively, stating that the contribution of all generators to response (rsp) and reserve (res), combined with the contributions from storage and DSR, needs to satisfy the system-level requirements for the two services.

$$\sum_{i=1}^{G} rsp_i^t + \sum_{i=1}^{S} (\alpha_{si}^{rsp} \cdot s_{-i}^t) + \sum_{i=1}^{D} \{\alpha_{d,i}^{rsp} \cdot (\mathrm{d}_i^t + d_{+i}^t - d_{-i}^t)\} \geq \underline{\mathrm{srp}}^t \tag{20}$$

$$\sum_{i=1}^{G} res_i^t + \sum_{i=1}^{S} (\overline{s}_i + \widehat{s}_i - s_{-i}^t) + \sum_{i=1}^{D} \{\alpha_{d,i}^{res} \cdot (\mathrm{d}_i^t + d_{+i}^t - d_{-i}^t)\} \geq \underline{\mathrm{srs}}^t \tag{21}$$

The amount of spinning and standing reserve and response is optimised ex-ante to minimise the expected cost of providing these services.

Power flow constraints (22) limit the energy flowing through the transmission system, respecting the total installed capacity as the upper bound. The model optimises the location and capacity of new transmission investment to minimise the objective function. Power flows are calculated as a function of net power injection, network topology and parameters.

$$-\left(\overline{\mathrm{f}}_i + \widehat{f}_i\right) \leq F(G,S,D)_i^t \leq \overline{\mathrm{f}}_i + \widehat{f}_i \quad \forall i \in F \tag{22}$$

Power flow is a function of power injections by generation, load and storage, and network topology and parameters. A linear expression of the power flow is given below (23).

$$F(G,S,D)_i^t = \sum_{j=1}^{N} \left({}^{\partial F_i}\!/_{\partial P_j} \cdot [g_j^t + s_{+j}^t - s_{-j}^t - d_{+j}^t - d_{+j}^t + d_{-j}^t] \right) \quad \forall i \in F \tag{23}$$

where ${}^{\partial F_i}\!/_{\partial P_j}$ is the sensitivity of the flow at corridor i with respect to power injection at node j.

Expanding transmission and interconnection capacity is generally found to be vital for facilitating the efficient integration of large intermittent renewable resources, given their location. Interconnectors provide access to renewable energy and improve the diversity of demand and renewable output on both sides of the interconnector, thus reducing the short-term reserve requirement. Interconnection also allows for sharing of reserves, which reduces the long-term capacity requirements.

The model can reinforce existing transmission links and add new capacity between previously unconnected regions (where the user allows). The model will reinforce both existing and new corridors if economically justified. Possible additions of new transmission lines between buses that are not initially connected would need to be specified by the user.

Reliability constraints ensure sufficient generating capacity in the system to supply the demand with a given level of reliability and estimate the loss of load expectation (LOLE). Figure 1 illustrates the use of piecewise linear functions to approximate the loss of load probability (LOLP) function. The LOLP curve, being a function of the capacity margin (CM), must be built a priori for a given system using a standard reliability approach. While the LOLP curve is not guaranteed to be convex, for the relatively low range of LOLP (e.g. below 20%), the curve can be represented quite accurately with a piecewise function as shown in Figure 1. The CM is the ratio of surplus generating capacity (including storage when it produces electricity) and the peak demand. Sharing of capacity between interconnected regions can also be considered to increase the CM.

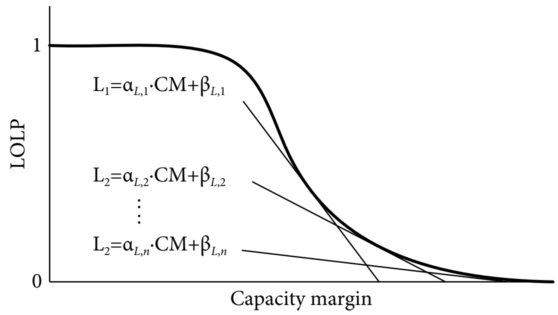

Fig. 1 Piecewise linear approximation of LOLP function.

Constraints (24) are used to approximate the LOLP, and the sum of LOLP across the year should meet the reliability criterion as defined by $\overline{LOLE}$ (25).

$$\begin{aligned} LOLP_i^t &\geq \alpha_{L,1} CM(\cdot) + \beta_{L,1} \\ &\cdots \\ LOLP_i^t &\geq \alpha_{L,n} CM(\cdot) + \beta_{L,n} \end{aligned} \tag{24}$$

$$\sum_{t=1}^{T} LOLP_i^t \leq \overline{LOLE}_i \tag{25}$$

2.2 Hydrogen system constraints

Hydrogen power balance constraint (26) ensures that hydrogen supply and demand, taking into account storage, are balanced at all times.

$$\sum_{i=1}^{H} h_i^t + \sum_{i=1}^{Sh} \left(sh_{+i}^t - sh_{-i}^t\right) - \sum_{i=1}^{Dh} \mathrm{dh}_i^t + \sum_{i=1}^{E} e_i^t = 0 \tag{26}$$

Constraint (27) limits the hydrogen production to be less or equal to the installed capacity. If needed, the model can reinforce the hydrogen production capacity.

$$h_i^t \leq \overline{\mathrm{h}}_i + \widehat{h}_i \tag{27}$$

Hydrogen storage constraints (28)–(31) are modelled the same way as for electricity storage (14)–(17).

$$sh_{+i}^t \leq \overline{\mathrm{sh}}_i + \widehat{sh}_i \tag{28}$$

$$sh_{-i}^t \leq \overline{\mathrm{sh}}_i + \widehat{sh}_i \tag{29}$$

$$esh_i^t \leq \left(\overline{\mathrm{sh}}_i + \widehat{sh}_i\right) \cdot \mathrm{sch}_i \tag{30}$$

$$esh_i^t = es_{hi}^{t-1} - sh_{+i}^t + \eta_{sh\,i} \cdot sh_{-i}^t \tag{31}$$

Hydrogen transport constraint (22) limits the hydrogen energy flowing through the hydrogen transmission system, respecting the total installed capacity as the upper bound. The model optimises the location and capacity of new hydrogen transmission investment to minimise the objective function. Hydrogen flows are calculated as a function of net hydrogen injection, network topology and parameters.

$$-\left(\overline{\mathrm{fh}}_i + \widehat{fh}_i\right) \leq Fh\,(H,Sh,Dh)_i^t \leq \overline{\mathrm{fh}}_i + \widehat{fh}_i \quad \forall i \in Fh \tag{32}$$

2.3 Carbon emission constraints

Equation (33) ensures that the annual carbon target is met by limiting the sum of residual emissions from electricity and hydrogen systems.

$$\sum_{t=1}^{T}\sum_{i=1}^{H} c_{hi}^{6} h_i^t + \sum_{t=1}^{T}\sum_{i=1}^{G} c_{gi}^{6} g_i^t - ghr \leq Carbon\ target \tag{33}$$

The optimisation problem defined in (1)–(33) has been implemented and solved using the FICO Xpress optimisation tool.[29]

3 Case studies

As LD-PHES is currently the most mature, proven long-duration LDES, the studies focus on the new LD-PHES in Scotland. However, it can be used as a proxy for other long-duration energy storage technologies such as compressed air, liquid air, flow batteries, seasonal thermal storage, and stacked blocks technologies.

The proposed approach is tested by running a spectrum of scenario-based studies to identify the key parameters that drive the system integration benefits of long-duration energy storage, looking at the impact of various scenarios on the value of LD-PHES using the future 2050 GB net-zero emission system background[30]. Annual non-heat and non-transport electricity demand is 367 TWh, heat energy demand (633 TWh termal), and transport-related electricity demand is 111 TWh. Heat supply is based on electric heating. Energy production, storage, network, and carbon infrastructure capacity and operation are optimised by the model. The scenarios considered in the studies are:

- Various LD-PHES designs with different aggregated power ratings and energy storage capacities. Six PHES configurations with 20–100 h durations are being studied:
  - 30 GWh storage with 300, 900, and 1500 MW power rating
  - 90 GWh storage with 900, 2700, and 4500 MW power rating
- A higher offshore wind penetration
- The presence of other flexibility technologies such as demand response
- Three prolonged periods (3, 7, 14 days) of extremely low-wind conditions during winter peak conditions

A system with no additional LD-PHES is used as a counterfactual scenario. The studies identify the system implications of the LD-PHES (how it will change the optimal portfolio of other technologies and infrastructure requirements, particularly the amount and value of the avoided investment in conventional and low carbon generation and transmission network between Scotland and England) and the value of benefits along the value chain, i.e. savings in operation cost through providing balancing services by the comparing the results of the study with the new LD-PHES against the counterfactual. In all cases, the energy system is optimised using the proposed approach.

3.1 System benefits

The results in Figure 2 demonstrate that the total annual system benefits of the new 30 GWh LD-PHES vary between 45 million to 121 million pounds per year in 2050 (depending on its power rating) than the counterfactual system's total cost. The saving with 90

GWh new LD-PHES is larger (between 200 million to 316 million pounds per year). It is important to note that the cost of new LD-PHES is not included, and therefore, the savings should be treated as gross savings that can be used to inform the investment case for the new LD-PHES.

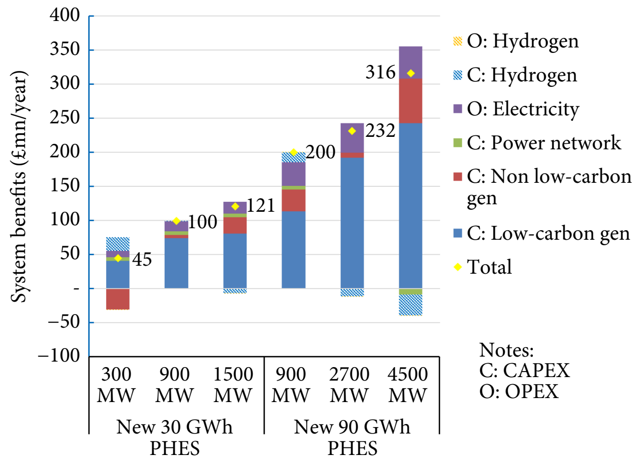

Fig. 2 System benefits of new LD-PHES.

Most of the savings come from the reduction of low-carbon generation (Capex of low-carbon gen). Avoided capital cost in electricity generation technologies makes up 75% of the value of new LD-PHES. In addition, there are other savings in reducing generation operating costs (Opex of electricity) and network reinforcement costs (Capex of power network). The results also indicate some impacts (positive in some cases and negative in others) on the hydrogen Capex and Opex demonstrating the sector coupling between electricity and hydrogen systems.

It is worth highlighting that most energy storage studies focused on the savings in electricity Opex. However, this study demonstrates that zero marginal cost renewables will dominate the 2050 system. Consequently, the electricity system cost will be Capex dominated. This finding highlights the importance of energy storage in influencing long-term system development and enabling more efficient investment in low-carbon technologies.

Comparing the benefits of 900 MW 30 GWh (33.3 h) with 900 MW 90 GWh (100 h) demonstrates the benefits of having a larger storage capacity. The benefits of 100 h storage capacity are double. However, the studies also demonstrate the benefits of having a higher power rating considering the same energy storage capacity.

3.2 Impact on the electricity generation portfolio

Figure 3 shows the changes in the electricity generation portfolio driven by the new LD-PHES. The results demonstrate that more wind power can be integrated with new LD-PHES. New LD-PHES brings more flexibility, improving the system balancing capability and reducing wind energy curtailment. Flexibility reduces the system integration cost of wind[31], making it more competitive. Therefore, it can increase the wind capacity that can be integrated into the system.

In terms of renewable integration, increased storage volume tends to be more important than increased power capacity. It demonstrates that LD-PHES facilitates the integration of wind power more effectively than shorter-duration storage. The increased volume of wind is not linear to the increase in the rating of LD-PHES. For example, 900 MW 30 GWh storage enables around 900 MW more wind power to be connected. Having a

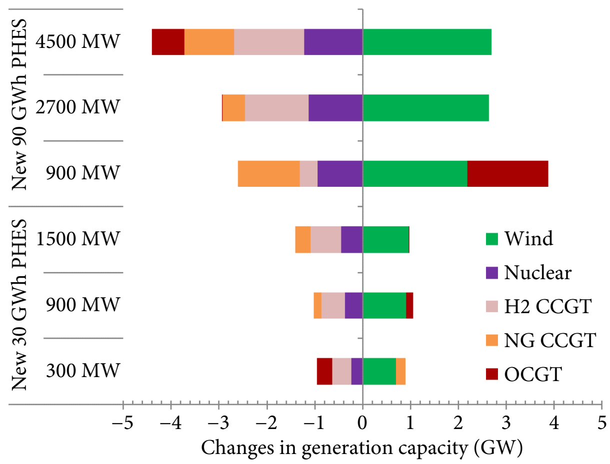

Fig. 3 Impact of new LD-PHES on power generation capacity.

higher power rating of the LD-PHES fleet to 1500 MW increases the new wind capacity slightly to around 1000 MW. However, increasing energy storage volume from 30 to 90 GWh enables 900 to 2200 MW wind capacity to be integrated.

LD-PHES acts to ‘firm up’ variable renewables, and therefore, the need for firm low carbon power generation (such as nuclear, hydrogen-based generation, CCS) is reduced. The volume of nuclear that can be displaced per MW of installed LD-PHES depends on the energy storage volume. For example, for the 100 h storage, between 0.75 to 1 MW nuclear capacity can be displaced by increased wind capacity supported by 1 MW LD-PHES. The ratio decreases to around 0.3 MW nuclear per MW LD-PHES for the 20 h storage.

LD-PHES has capacity value, and therefore, it can displace firm generation capacity. Studies demonstrate that the capacity value of storage depends not only on the power rating of the storage but also on the energy storage capacity as it has to cover the duration of the peak demand. In this study, the 20 to 100 h of energy storage capacity is sufficient to maximise its capacity value.

Some CCGT capacity can also be displaced by OCGT running with green gas as the CCGT capacity factor decreases along with the increased wind penetration. It is important to highlight that the capex of CCGT is higher than the OCGT capex, and therefore, it may be more cost-efficient to displace low load factor CCGT with OCGT using green gas.

3.3 Impact on the electricity generation portfolio

LD-PHES in Scotland can also provide a service to manage transmission network congestion, for example, at the Scotland–England border. When the network is congested during high wind periods, the LD-PHES can store the wind energy to relieve the congestion and discharge the energy back to the grid during low-wind conditions. Using the proposed approach, the volume of transmission capacity needed and the implications of the new LD-PHES to the capacity needed can be quantified and analysed.

In this context, the model calculates the required capacity of the Scotland-England interconnectors for different cases, and the results are shown in Figure 4.

Without the new LD-PHES plants, the counterfactual system will require a total interconnection capacity of around 10.8 GW between Scotland and England in 2050 compared to circa 6 GW today. With new LD-PHES plants, the transmission capacity required reduces, as shown in Figure 4. For example, with 900 MW 30 GWh storage, the total capacity required decreases to 10.4 GW.

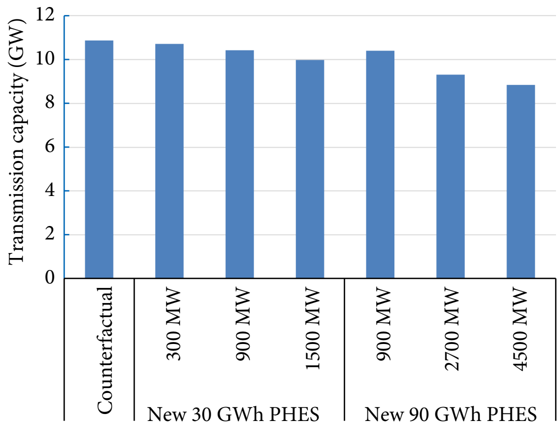

Fig. 4 Impact of new LD-PHES on Scotland–England boundary transfer capability requirements.

The capacity required does not change when the storage capacity increases to 90 GWh. However, if the rating of LD-PHES is 4500 MW (although with the same 90 GWh energy storage), the total transmission capacity requirement decreases by 2 to 8.8 GW. It is important to note that storage may have capacity benefits across multiple system boundaries.

The results demonstrate that the benefit of the LD-PHES in providing network congestion management correlates more strongly to the rating of the LD-PHES, although the benefit also diminishes along with the increased capacity of new LD-PHES. Although it is not demonstrated in the study, we can conclude that sufficient storage capacity is also required since there may be a need to reduce the flows for several hours. Given the assumptions taken in the study and the assumed storage capacity (20–100 h), the results show that such capacity is sufficient for transmission congestion services.

3.4 Impact on the hydrogen storage requirements

Power-to-gas (electrolysers) and hydrogen-based power generation create links between the electricity and hydrogen systems. The flexibility in the hydrogen system provided by hydrogen storage can benefit the electricity system. On the other hand, since part of the hydrogen demand potentially comes from power generation, the electricity system's flexibility that changes the temporal variation of hydrogen demand may also affect the need for hydrogen storage. In this context, we investigate the impact of LD-PHES on the need for hydrogen storage in the system. The results are presented in Figure 5.

In this study, hydrogen is used to fuel power generation. The main source of hydrogen is bioenergy through gasification with carbon capture and storage. The biomass plants run at a high load factor to reduce their capex but the hydrogen demand for power generation (around 93 TWh/year) varies in time depending on, among others, wind power output. Therefore, hydrogen storage is needed to enable supply and demand balance in the hydrogen system.

As shown in Figure 5, the integration of new 30 or 90 GWh LD-PHES reduces the need for hydrogen storage by around 70 GWh in the case with 30 GWh LD-PHES. Increasing the power rating of LD-PHES has a small impact. A similar pattern is found with the 90 GWh LD-PHES; it reduces the hydrogen storage requirement by around 110 GWh. The reduction is not linear to the increased LD-PHES capacity since the whole system evolves and is optimised by the model.

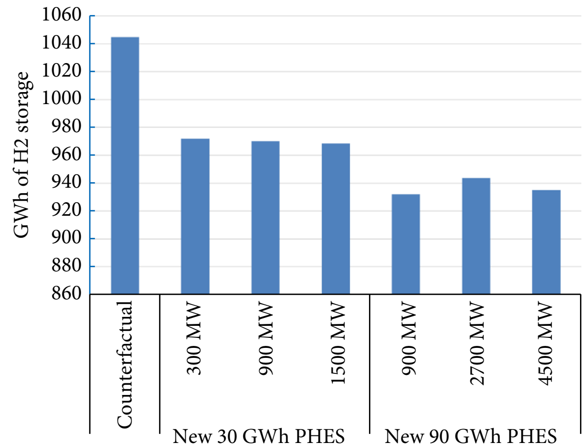

Fig. 5 Impact of LD-PHES on the requirement of hydrogen storage.

While hydrogen storage can provide low-cost bulk energy storage, converting electricity to hydrogen and back to electricity incurs substantial losses. The overall energy conversion efficiency is only 40%–50%. In comparison, the efficiency of LD-PHES is above 75%. Therefore, it is expected that both technologies will work complementarily, although to a certain extent, also compete.

3.5 Impact of low-cost offshore wind

Demand for system flexibility is triggered by the increased penetration of variable and intermittent generation from renewables and the need to meet the emission target. In this context, we investigate the impact of increasing total wind capacity (including both onshore and offshore wind) connected to the Scotland grid by reducing the LCOE of wind on the value of new LD-PHES. Two cases are investigated: (i) 30 GW of wind generation connected in Scotland (offshore and onshore) out of 77 GW of wind (offshore and onshore) connected across GB, and (ii) 52 GW of wind (offshore and onshore) connected to Scotland infrastructure out of 120 GW wind (offshore and onshore) connected across GB. The cases with 30 and 90 GWh of energy storage are presented in Figure 6.

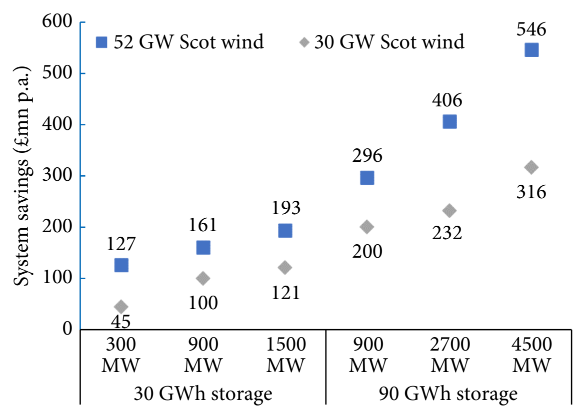

Fig. 6 Impact of higher wind penetration on the value of LD-PHES.

As expected, the cost savings attributed to the new LD-PHES increase considerably with a higher wind power penetration. For example, for the 900 MW 30 GWh storage, the savings increase from around £100m to £161m per year. The impact is more profound in the 90 GWh storage case as the system relies more on the flexibility provided by storage; the system benefits of LD-PHES are up to £546m/year.

Considering the rapid development of offshore wind in the UK driven by the cost reduction and improvement of technologies, it can be expected that further penetration of wind farms in Scotland may boost further the value of LD-PHES. The emergence of floating offshore wind farms that can release the full potential of wind resources in the UK's waters can drive additional value for LD-PHES in the future.

3.6 Impact of other flexibility technologies such as demand response

A set of studies is used to investigate the impact of other flexibility technologies on the value of new PHES. We assume no increased demand response in an inflexible system compared to today, no new energy storage except the new PHES. The study assumes a high demand response in the flexible system, and the model is allowed to install new battery storage if needed. The demand response comes from different sources, including industrial and commercial customers (3.5%), electric vehicles (40%), and smart appliances (20.5%). In this study, the demand response provides short-term flexibility as some percentage of the energy demand can be shifted within one day. Demand response can also provide frequency response and balancing services. Thus, the demand response-based services compete directly with the flexibility services from the new PHES. The cost of demand response is negligible, and the efficiency losses due to load-shifting are assumed to be small.

Using the same approach as described previously, we quantify the value of new PHES under two system conditions: an inflexible and flexible system. The 30 and 90 GWh energy storage capacity results are compared and presented in Figure 7. The results show that the system benefits of the new PHES are much lower in a flexible system than in an inflexible system. Consequently, the impact on the system savings will also be reflected in the savings per MW PHES. For example, for the 900 MW 30 GWh storage, the benefit is around £100m/year in the flexible system. Without other flexibility technologies, the benefit increases to around £190m/year; the difference is £90m/year. The finding is the same for the 90 GWh storage, but the difference tends to be higher. For example, for the 2700 MW 90 GWh storage, the benefit is around £231m/year; this value increases to £481m/year in the inflexible system; the difference is £250m/year.

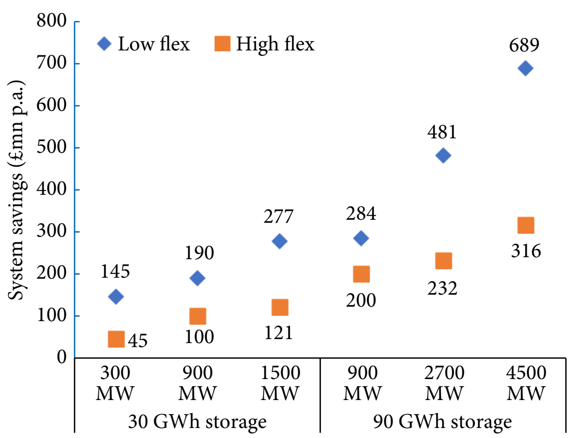

Fig. 7 Value of new LD-PHES in a flexible and inflexible energy system.

The impact of other flexibility technologies is also more profound with the short-duration storage. The results are expected since the shorter duration storage will compete more strongly to demand response and battery storage. In conclusion, these findings highlight that LD-PHES is still valuable and complementing the presence of other short-duration flexibility technologies.

3.7 Impact of a prolonged period of extremely low wind conditions

The analysis demonstrates how LD-PHES can be dispatched to generate electricity during 3-days low-wind conditions which coincide with the peak demand. LD-PHES can generate electricity for a few days without the need to be charged during that period. This characteristic is essential, especially if there is a prolonged period of low-availability of renewable energy resources or generation capacity. In this context, the charging and discharging cycle of LD-PHES, electricity demand, and electricity production from different generation technologies are plotted in Figure 8 for a winter week where the peak demand coincides with a 3-day low-wind period.

The upper graph of Figure 8 shows the output of different generation technologies and electricity production from LD-PHES (2 GW, 100 h). On day 16–18, wind output is very low while the electricity demand is at the peak, as shown by the lower graph in the same figure. To meet the peak demand on those days, the long-duration storage produces electricity supporting other generation technologies. Peaking generation such as OCGT running on biogas (considered as carbon-neutral), H2 OCGT running on hydrogen, and electricity import are also used to meet the demand during those days. Without sufficient energy storage, the system will require the additional capacity of firm low-carbon generation technology (such as nuclear, hydrogen-based generation, CCS). The finding highlights the difference between the short-duration (1–4 h) storage with longer-duration storage. On day 16–18, the storage is not being charged as baseload plants' capacity has been fully employed. For example, when the wind blows again on days 19-20, the storage is charged.

However, there is uncertainty on how long the low-wind period during peak demand may occur in future[1]. In this context, we carry out further analysis by extending the period of extremely low-wind output to one week and two weeks to investigate the impact on the value of LD-PHES. The system savings attributed to the 2 GW 200 GWh storage for a system designed to withstand prolonged low-wind periods during peak demand are shown in Figure 9.

The value of 2 GW 200 GWh LD-PHES does not change significantly when the low-wind duration is extended from 3 days to 1 week. The results are expected considering that 100 h energy storage can provide continuous support for one week, considering the diurnal variation of electricity demand. Extending the low-wind period to 2 weeks substantially impacts the storage benefits; the savings plummet from around £371m to £121m per year.

The results demonstrate that the value of long-duration storage depends on the energy storage capacity. The benefit will be less if the capacity is too small relative to system needs. If the duration of no wind events increases, the system will require more energy storage capacity to deal with it. In order to deal with a two-week low-wind period, longer duration storage will be required. Without sufficient capacity, the storage cannot substitute firm low-carbon generation (such as nuclear, hydrogen-based generation, CCS) and reduce the system costs.

4 Conclusions

A novel integrated formulation of electricity and hydrogen systems is proposed to support analyses of the roles and quantify the value of long-duration energy storage holistically. A spectrum of

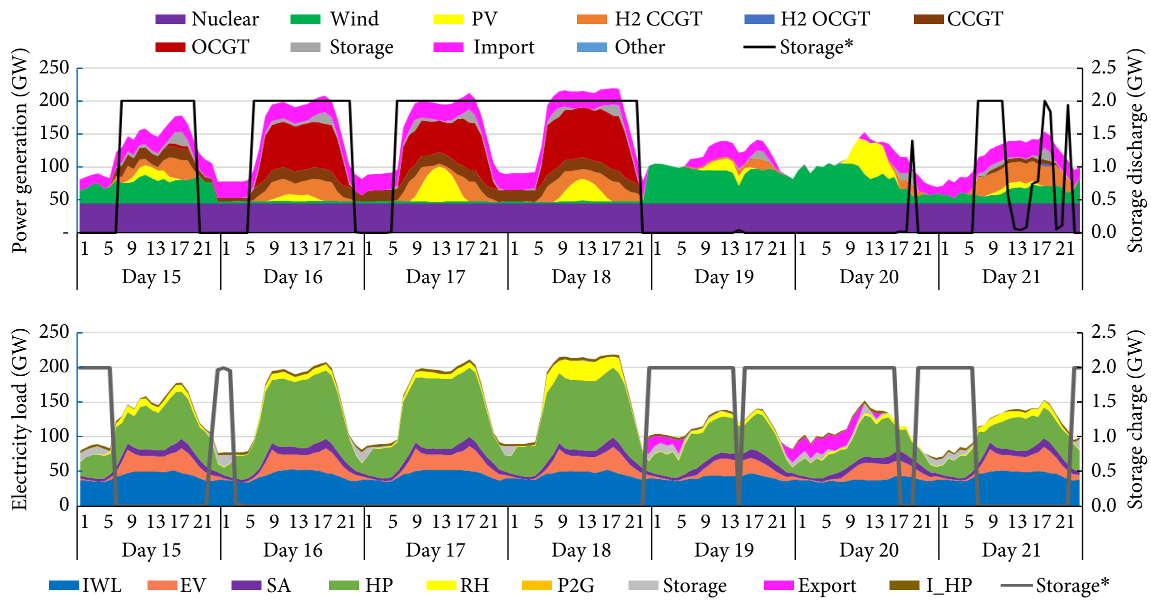

Fig. 8 Charging and discharging of LD-PHES in a winter week with peak demand.

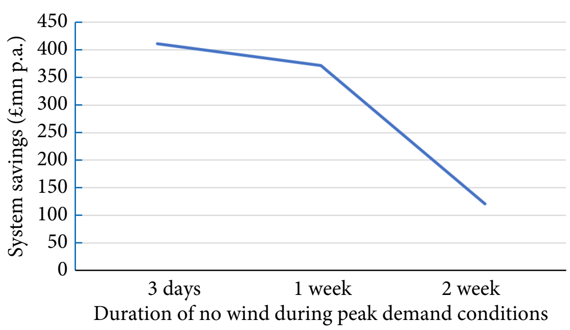

Fig. 9 System savings of LD-PHES in a system with prolonged periods of extremely low-wind conditions.

case studies has been performed using the proposed approach on a future 2050 net-zero emission system background of Great Britain (GB) with a high share of renewable generation and analysed to identify the value drivers, including the impact of prolonged low wind periods during winter, the impact of different designs of LDES, and its competitiveness and synergy with other technologies. The results demonstrate:

- The importance of energy storage in influencing long-term system development and enabling more efficient investment in low-carbon technologies. Most of the benefits are savings in low-carbon generation investments;
- Longer duration storage can facilitate more variable RES;
- The system benefits of the new PHES are much lower in a flexible system than in an inflexible system. There is competition with other flexibility resources.
- The value of LD-PHES reduces when the low-wind duration exceeds the storage capacity to provide continuous support to the system. Storage can also provide firm capacity for supply reliability as long as it has sufficient storage capacity behind it.

Appendix

Nomenclature

A. Constants

α_d	Ratio of flexible electricity demand to total demand
α_d^{rsp}	Proportion of flexible loads that can be interrupted to provide frequency response
α_d^{res}	Proportion of flexible loads that can be interrupted to provide operating reserves
α_s^{rsp}	Proportion of storage charging that can be interrupted to provide frequency response
$(\alpha, \beta)_{L,n}$	Linear coefficient and constant term for the n-th piecewise linear approximation of LOLP function
η_d	Demand-Side Response (DSR) efficiency [%]
$\eta_s[\eta_{sh}]$	Electricity[hydrogen] storage efficiency [%]
$\bar{\mu}$	Number of existing generating units
$\pi_{\widehat{dn}}$	Distribution network reinforcement cost per unit
$\pi_{\hat{f}}$	Transmission network reinforcement cost per unit
π_g	Generation operating cost per unit
$\pi_{\hat{h}_i}$	Per unit CAPEX of hydrogen production capacity of unit i
$\pi_{\hat{\mu}}$	Generation investment cost per unit
π_{nl}	Generation no-load-cost
$\pi_{\hat{s}}$	Storage investment cost per unit
π_{st}	Generation start-up cost
τ	Total time horizon [h]
c^6	Carbon emissions per unit energy produced [$kgCO_2$/MWh]
d	Electricity load [MW]
dh	Hydrogen load [MW]
$\bar{f}$	Existing transmission network capacity [MW]
$\underline{g}$	Minimum stable generation [MW]
$\bar{g}$	Power rating of a generating unit [MW]
LF	Load factor of a generator
r_{dn}	Ramp-down limit [MW]
r_{up}	Ramp-up limit [MW]
$\overline{rsp}$	Maximum response limit [MW]
$\bar{s}$	Existing storage capacity [MW]
sc	Number of hours that storage can produce electricity at maximum power (i.e. storage duration)
srp	System frequency response requirement
$\underline{srs}$	System operating reserves requirement
$\underline{Dn}$	Minimum downtime [h]
Up	Minimum uptime [h]

B. Variables

μ	Number of units in operation
$\hat{\mu}$	Number of additional generating units installed
d_+	Increased electricity load due to DSR [MW]

d_-	Reduction in electricity load due to DSR [MW]
ds	number of generating units being de-synchronised
e	Electrolyser load [MWh]
$es[esh]$	Energy content of electricity[hydrogen] storage [MWh]
$\hat{f}\,[\hat{fh}]$	Additional electricity[hydrogen] transmission network capacity [MW]
g	Electricity production [MW]
ghr	volume of carbon emissions removed [kgCO_2 p.a.]
h	Hydrogen production [MW]
$\hat{h}_i$	Hydrogen production capacity of unit i [MW]
res	Spinning reserve provided by generators [MW]
rsp	Frequency response provided by generators [MW]
$s_+\,[sh_+]$	Electricity[hydrogen] generated by storage [MW]
$s_-[sh_{h-}]$	Electricity[hydrogen] consumed by storage [MW]
$\hat{s}[\hat{sh}]$	Additional electricity[hydrogen] storage capacity [MW]
st	number of generating units being synchronised
CM	Capacity margin [MW]
$LOLP$	Estimated Loss of Load Probability (LOLP)

C. Functions

$C_g(\bullet)$	Generation operating cost function
$F(\bullet)$	Power flows function

D. Sets

$D[Dh]$	Set of electricity [hydrogen] demand
E	Set of electrolysers
$F[Fh]$	Set of electricity [hydrogen] transmission corridors
G	Set of generators
H	Set of hydrogen production technologies
N	Set of nodes
$S[Sh]$	Set of electricity [hydrogen] storage devices
T	Set of operating snapshots

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Additional information

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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